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METHODOLOGIES AND APPLICATION

A type-2 fuzzy logic recommendation system for adaptive teaching

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Abstract E-learning platforms facilitate the interaction between students and instructors while mitigating temporal or spatial constraints. Nevertheless, such platforms require measuring the degree of students' engagement with the delivered course content and teaching style. Such information is highly valuable for evaluating the quality of the teaching and altering the teaching delivery style in massively crowded online learning platforms. When the number of learners is high, it is essential to attain overall engagement and feedback, yet doing so is highly challenging due to the high levels of uncertainties related to students and the learning context. To handle these uncertainties more robustly, we present a method based on type-2 fuzzy logic utilizing visual RGB-D features, including head pose direction and facial expressions captured from Kinect v2, a low-cost but robust 3D camera, to measure the engagement degree of students in both remote and on-site education. This system augments another self-learning type-2 fuzzy logic system that helps teachers with recommendations of how to adaptively vary their teaching methods to suit the level of students and enhance their instruction delivery. This proposed dynamic e-learning environment integrates both on-site and distance students as well as teachers who instruct both groups of students. The rules are learned from the students' and teachers' learning/teaching behaviors, and the system is continuously updated to give the teacher the ability to adapt the delivery approach to varied learners' engagement levels. The efficiency of the proposed system has been tested through various real-world experiments in the University of Essex iClassroom among a group of thirty students and six teachers. These experiments demonstrate the capabilities—compared to type-1 fuzzy systems and non-adaptive systems—of the proposed interval type-2 fuzzy logic-based system to handle the uncertainties and improve average learners' motivations to engage during learning.

Keywords Type-2 fuzzy logic systems · E-learning · Student engagement · 3D vision

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1 Introduction

Recently, the teacher's role has moved from one where they know everything to one where teachers must be continuously learning and reflective on their skills (Mergler and Spooner-Lane 2012). The teacher's role in the learning environment has been found to be the most influential aspect in improving student satisfaction, outcomes, and engagements (Hattie 2003; Lovat 2007). Thus, most teachers aim to improve their teaching skills, which have been acquired through their pre-service teaching qualification, training, and career expertise (Mergler and Spooner-Lane 2012). However, our understanding of what constitutes quality teaching has changed over time, and the definition has become more challenging (Lovat 2007). Thus, it is difficult to get definite feedback about the best instructional approaches that teachers can follow to promote different learners' engagement, outcomes, and satisfaction due to several issues associated with teachers, learners, and technology-mediated learning and their interactions in the teaching-learning process. First is the issue of teacher expertise in evaluating various learners' engagements as well as the best instructional approaches and teaching actions to maintain the various learners' engagement in a balanced and improved way. Even if teachers profess to have high learner engagement, they will, under normal circumstances, receive no feedback about the engagement of remote learners. Moreover, the total size of remote and on-site students makes it difficult for teachers to diagnose students' interests and discover the best instructional actions to motivate them regarding the learning objectives.

Similarly, beginning teachers step into an unknown world, working under the obligation to teach learners with different needs and levels of engagement, and this variable can cause them apprehension (Smith and Sela 2005). This is because there is no smooth initiation into teaching and many teachers struggle to progress from pre-service training to professional practice (Smith and Sela 2005). Importantly, new teachers are usually required to teach like experienced teachers, and thus face the multiple tasks of being students, instructors, and scientists (Öztürk and Yildirim 2013). Although novices do not have the qualities of experienced teachers, they are still required to meet similar requirements as soon as they enter the field. Furthermore, the most difficult or irksome teaching assignments are often dumped on newly qualified teachers and junior staff members (Öztürk and Yildirim 2013). The immense stress resulting from these factors results in the situation whereby new teachers leave the teaching job at higher rates than new workers in other fields (Wonacott 2002).

High teacher stress and turnover affects student learning in terms of achievement, engagement, and, ultimately, the outcomes comprise the end result of the education system. Recently, with advances in educational technology, adaptive educational systems have emerged, and, despite being intended for use by individual students in asynchronous learning contexts, such systems can be used to tailor instructional content to the needs of each student, thus promoting improved learning performance (Shute and Zapata-Rivera 2012; Intelligent Adaptive Learning 2012). Drawing on the ideas underpinning these adaptive systems that learn what works best for students, we extend a synchronous system to adaptive teaching and training that enables teachers to learn the behaviors of expert teachers in tackling different students' engagement in accordance with variables of the course content. This process will open opportunities for professional growth for teachers and enhance instruction, which will lead to better student achievement and promote student engagement.

A higher level of engagement with the course content and teaching instructions enables students to acquire more knowledge, therefore improving their learning performance (Clark and Mayer 2011). As such, maintaining and increasing the learning engagement of different students requires ongoing learning in the context of the instructions established by experienced teachers. Given these considerations, the purpose of this study is to identify the instructional approaches that experienced teachers, in light of general course characteristics and different student engagement levels, deem to be the most effective. Subsequently, this learned behavior can be applied in the training of new teachers to improve their teaching approaches and thus promote better learning.

The effectiveness of any adaptive and intelligent teaching framework depends on the approach used to accurately accumulate data about the best instructional approaches, and also the ability of learning how and when this information is processed to prepare an effective instruction context (Shute and Zapata-Rivera 2012). The important question arises, then, of how one can ensure precision in evaluating and choosing the appropriate teaching approach that will best promote and improve learner engagement. This question is quite critical because of uncertainties about how accurately teacher decisions about instructional approaches are actually categorized by the learning system—as well as the corresponding uncertainties associated with how the resulting instruction is actually decided and administered according to the varied levels of learner engagement.

In synchronized teaching environments, there are high levels of linguistic uncertainties whereby teachers can interpret and act on the same terms, words, or methods (e.g., pertaining to lesson difficulty, appropriate teaching style, and approach) in various ways, according to their pupils' varied levels of engagement, knowledge, and expertise in their subject. The integration of flexible Artificial Intelligence (AI) techniques within adaptive e-learning contexts could help to handle the uncertainties that may negatively affect the development of an environment which encourage learning and teaching (Ahmad et al. 2004).

To the best of our knowledge, no previous studies have been proposed to learn the teaching behavior process according to the varied on-site and distance learners' levels of engagement in their respective learning environments. Fuzzy logic systems are well known for their ability to generate white box models that can handle high levels of uncertainty. However, the vast majority of fuzzy logic systems employ type-1 fuzzy logic systems, which handle the encountered uncertainties via the precise type-1 fuzzy sets. In contrast, Interval Type-2 Fuzzy Logic Systems (IT2FLSs) can handle the uncertainties encountered through interval type-2 fuzzy sets, which are characterized by a Footprint of Uncertainty (FOU) that provides an extra degree of freedom in handling high uncertainty levels.

This paper presents an IT2FLS capable of understanding various teachers' behaviors, involving their instructional decisions in accordance with various varied learners' average engagement levels and the difficulty level of the content in dynamic teaching environments. The type-2 fuzzy model is first created from data collected from a number of teaching sessions with different teaching approaches conducted by different qualified teachers. The learned type-2 fuzzy-based model is then used to improve instructional delivery approaches that can be used as supplemental tools to aid the teaching profession and enhance the learning process. We will show how the proposed system enables the customization of instructional delivery to improve and increase different learners' engagement. Furthermore, the proposed system is flexible enough to allow constant updating in accordance with the level of student engagement. A number of experiments have been conducted within the iClassroom at the University of Essex among a group of thirty students and six teachers to assess the efficiency of the proposed system. The results of the experiments indicate that, in comparison to type-1 fuzzy systems and non-adaptive systems, the proposed system based on interval type-2 fuzzy logic has greater capacity for managing ambiguities and stimulating student engagement and satisfaction.

Section 2 will present a brief overview on the need to consider students' engagement degree according to the teaching approaches in E-learning environments. A brief overview of interval type-2 fuzzy logic systems is presented in Sect. 3. Section 4 explains the proposed type-2 fuzzy logic-based recommendation system for adaptive teaching across interactive E-learning environments. Section 5 describes the experiments and results while conclusions and future work are presented in Sect. 6.

2 The need to consider students' engagement degree according to the teaching approaches in e-learning environments

Awareness of student-related variables and how those variables can be improved is important when trying to determine the optimal instructional approaches in different teaching contexts. The personalisation variables of students that need to be adjusted in the context of learning and the pedagogic personalisation strategies used to handle those variables can be found in Shute and Zapata-Rivera (2012) and Essalmi et al. (2010).

Currently, e-learning is confronted by a significant limitation, in that student engagement is not taken into account by learner models, and do not map delivery needs in terms of the appropriated instructional approach. However, it is unreasonable to expect the teacher to track each individual learner especially in the online-learning where the number of students are high. Therefore, automatically gaining and analyzing the objective feedback from the attendees is the key step in the procedures of education so that adaptive and personalized education is delivered. Several methods were proposed where in Mayberry et al. (2014) and Ye et al. (2012), wearable sensors embedded into the glasses facing towards users' eyes were used to analyze the eye gaze and the interests of the users. In Hardy et al. (2013), skin conductance sensors were employed to recognize the connection between the biological degree of skin conductance and emotional experiences in a training session of training and learning systems. Similarly, in Mota and Picard (2003), a particular chair utilizing pressure sensors was developed to understand the regular body actions to relate a child's interest level in the procedure of conducting an education session on a computer. This system was also utilized in Mello and Graesser (2009) to observe the students' body gestures for recognizing the students' emotions in a learning session. In Amershi et al. (2006), a system based on hybrid wearable sensors sensing the real-time data of skin conductance, heart rate, and EMG was proposed and this system used an unsupervised feature selection algorithm to measure learner engagement. However, wearable electronic devices are intrusive and uncomfortable for the users especially those electronic devices are required to deploy near the sensitive parts of the human such as eyes.

A conventional non-contact method to estimate the engagement degree is to analyze the eye-gaze features. In Corcoran et al. (2012), eye-gaze direction was calculated based on 2D video data using low-cost embedded hardware platform to determine the engagement and reaction of the users in gameplay so that feedbacks can be provided into the gaming user interface and gameplay logic. In Asteriadis et al. (2009), the learner's engagement level was estimated and classified for the application scenarios of human-computer interaction by a webcam using the features extracted from 2D user images including head pose, eye gaze, eyebrow and head movements, mouth opening statues, etc. In Hernandez et al. (2013), users' engagement level was estimated by the 2D camera images based on the extracted facial features and the output results was labeled into four different levels of engagement. However, 2D image-based methods are inadequate for returning robust features to complex vision applications such as eye gaze recognition. Therefore, higher level systems using multiple hybrid sensors are studied.

In Ishii et al. (2014), an engagement estimation system based on a particular eye-gaze tracking device was proposed. This system is able to robustly measure the user's engagement based on the orientation of the eye gaze captured by a particular non-contact device. However, the main disadvantage is due to its high expense (around \$2000 USD per piece) of this type of sensor which can be only used for single user within a relatively short distance (60 centimetres). A similar method was reported in Mello et al. (2012) where engagement analysis system based on eye tracker was proposed and this system is able to label the student as not engaged if the student looked away from the screen.

Besides the engagement analysis methods using various sensors, there are literatures reporting the systems based on sensor-free methods for estimating the students' engagement. In Baker (2012), an engagement and emotion analysis system based on machine learning was developed to detect the user's emotional state such as bored, engaged, not engaged, confused, and frustrated. The system employs data mining techniques analyzing the logs data which covers the information of the student activities such as the time length the student spends on finishing the question, the difficulty level of the question, and the correctness of the answer given by the student. However, these methods are not substantially better especially when subject to stringent cross-validation processes (Baker 2012). A similar engagement detection method was presented in Badge et al. (2012) based on academic activities and log information of learners performed in a social network.

To address the problems discussed above, in this paper, we introduce an engagement estimate system using non-contact, low-cost, and multi-user-support 3D sensor Kinect v2 which is capable to capture reliable features including head pose direction and hybrid features of face expression enabling the convenient and robust estimation of engagement based on IT2FLS in large-scale online and on-site learning in an unconstrained and naturalistic environment where users are allowed to act freely and move without restrictions.

3 A brief overview of type-2 fuzzy logic systems

The Interval Type-2 Fuzzy Logic System (IT2FLS) depicted in Fig. 1a uses interval type-2 fuzzy sets (such as the type-2 fuzzy set shown in Fig. 1b) to represent the inputs and/or outputs of the FLS. In the interval type-2 fuzzy sets all the three dimension values are equal to one. The use of interval type-2 FLS helps to simplify the computation (as opposed to the general type-2 FLS) (Mendel 2001).

The interval type-2 FLS works as follows: the crisp inputs are first fuzzified into input type-2 fuzzy sets; singleton fuzzification is usually used in interval type-2 FLS applications due to its simplicity and suitability for embedded processors and real-time applications. The input type-2 fuzzy sets then activate the inference engine and the rule base to produce output type-2 fuzzy sets. The type-2 FLS rule base remains the same as for the type-1 FLS, but its Membership Functions (MFs) are represented by interval type-2 fuzzy sets instead of type-1 fuzzy sets. The inference engine combines the fired rules and gives a mapping from input type-2 fuzzy sets to output type-2 fuzzy sets. The type-2 fuzzy output sets of the inference engine are then processed by the type-reducer, which combines the output sets and performs a centroid calculation which leads to type-1 fuzzy sets called the type-reduced sets. There are different types of type-reduction methods. In this paper we will be using the Center of Sets type-reduction as it has a reasonable computational complexity between the computationally expensive centroid type-reduction and the simple height and modified height type-reductions, which have problems when only one rule fires (Mendel 2001). After the type-reduction process, the type-reduced sets are defuzzified (by taking the average of the type-reduced sets) to obtain crisp outputs. More information about the interval type-2 FLS can be found in Mendel (2001).

The shaded area in Fig. 1b is labeled as Footprint of Uncertainty (FOU) which is bounded by lower membership function $\underline{\mu}_{\tilde{A}}(x)$ and an upper membership function $\bar{\mu}_{\tilde{A}}(x)$ (Mendel 2001). Thus an interval type-2 fuzzy set is written as follows:

$$\tilde{A} = \int_{x \in X} \left[\int_{u \in \left[\underline{\mu}_{\tilde{A}}(x), \bar{\mu}_{\tilde{A}}(x)\right]} 1/u \right] / (x). \qquad (1)$$

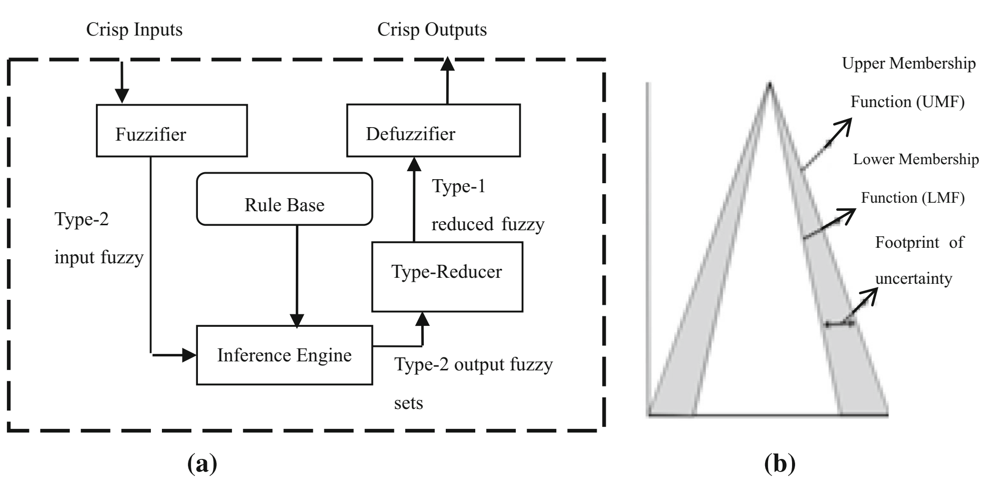


Fig. 1 **a** Structure of the type-2 FLS (Mendel 2001). **b** An interval type-2 fuzzy set

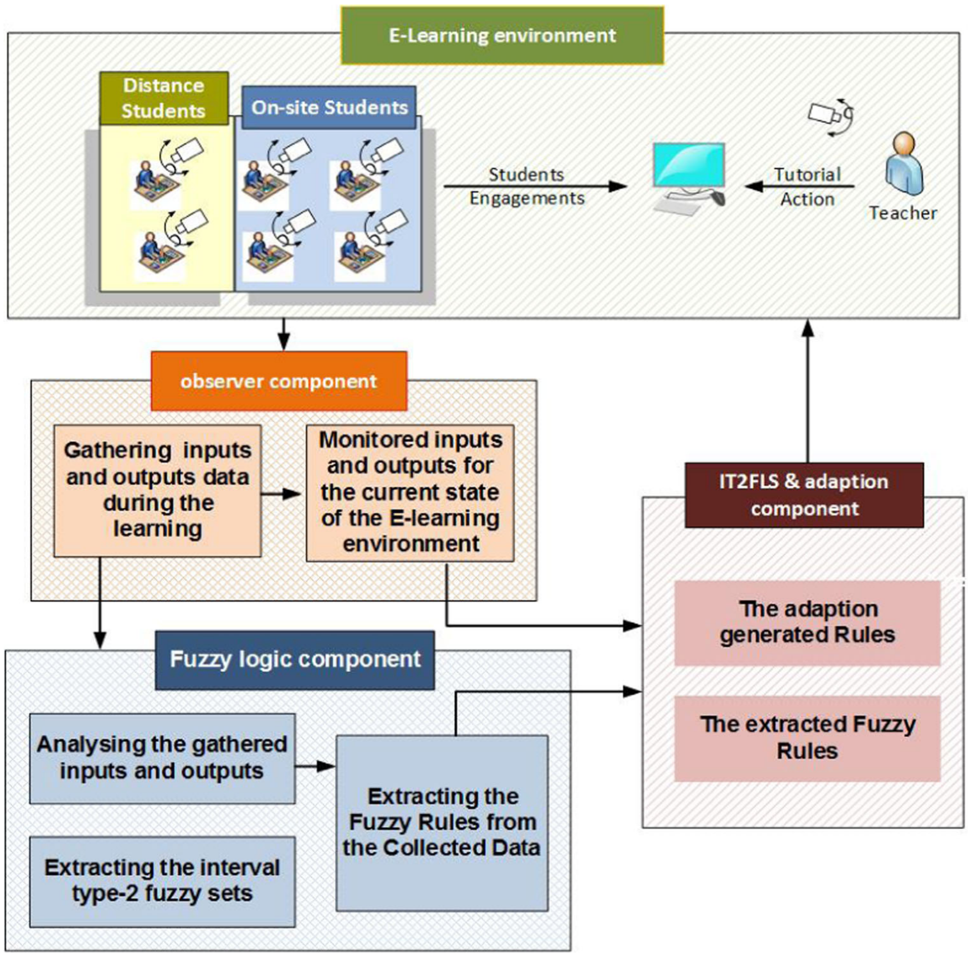


Fig. 2 An overview on the proposed type-2 fuzzy logic based recommendation approach for adaptive teaching across interactive e-learning environments

4 The interval type-2 fuzzy logic based recommendation system for adaptive teaching across interactive e-learning environments

Throughout the proposed e-learning framework, knowledge acquisitions would be transformed based on the teacher's instructional approaches and tutorial actions aimed at fulfilling and prompting the current feedback regarding the varied levels of engagement of the remote and on-site learners. Figure 2 shows the conceptual model of the proposed environment whereby the data about the appropriate instructional approach are recorded by the tutor according to the distance and on-site learners' varied engagement levels and the lesson's difficulty level (for the three teaching sessions in the case of the carried out experiments) in the observer component. In this component, the data from the e-learning framework are monitored and captured at whatever point the teacher alter his or her instructional approach. Accordingly, these gathered data will be used in the fuzzy learning component. This component will initially enable the system to generate the type-2 fuzzy sets as per the methodology described in Liu et al. (2007), Almohammadi et al. (2014) and Almohammadi and Hagras (2013b).

This method centers on producing type-2 fuzzy sets via the gathering of type-1 fuzzy sets from various instructors. These type-1 fuzzy sets are combined, resulting in the FOU, which appropriately induces a type-2 fuzzy set, which is seen to signify a word. Furthermore, this component implements an unsupervised one-pass approach, as inspired by Wang (2003), Hagras et al. (2007) and Almohammadi and Hagras (2013a), and obtains the rules from the acquired data; this is the main goal of this component. In the IT2FLS adaptation rules component, these learned rules trigger the best instructional methodologies based on the current state of inputs. This adaptation model component also considers the new teacher-learned actions that are subject to the existing input parameters from the e-learning environment that are already monitored in the observer component, and subsequently creates an output in consideration of the current state of inputs. This further enables the online adaptation and enhancement of rules and ultimately facilitates life-long learning owing to the dynamic quality of teaching and learning process interactions.

As demonstrated in Fig. 2. There would be three components in the proposed system which are the observer component, the fuzzy logic component, and the IT2FLS and adaptation components. These three components will be discussed in detail in the following subsections.

4.1 The observer component

Primarily, the proposed system gathers and captures the data through collecting the appropriate instructional approach as recorded by the teacher, according to the distance learners' varied average level of engagement and the difficulty level of the current lesson taught within the online learning environment. It is noteworthy that the data (both current inputs and outputs) would be actively recorded by the system if there was any change in the appropriate instructional approach (as indicated by the teachers) in accordance with the current state of the e-learning environment. Thus, our system creates and learns a descriptive model of the best instructional teachers' methodologies used in tackling and promoting the varied levels of engagement of distance learners in a balanced way; this is achieved through the data gathered, generating a set of multi-input and multi-output data pairs, which take the following form Wang (2003), Hagras et al. (2007) and Almohammadi and Hagras (2013a):

$$x^{(t)};\ y^{(t)} \quad (t = 1, 2, \ldots, N), \tag{2}$$

where N is referred to as the total of data instances, $x^{(t)} \in R^n$, and $y^{(t)} \in R^k$. Rules are basically mined by our system, which explains how the k output, which is the best instructional approach variables $y = (y_1, \ldots y_k)^T$ are affected by the input variables $x = (x_1, \ldots x_n)^T$. A model mapping inputs to outputs is achieved using the established fuzzy rules without requiring a mathematical model. Therefore, individual rules can be adapted online, affecting only certain aspects of the descriptive model created and learned by the proposed system.

4.1.1 The proposed method for engagement degree estimation

The first step is to calculate the head pose orientation and the face emotion using the SDK of Kinect v2. After that, the deviation degrees of the current head orientation away from the expected direction (towards the whiteboard or screen) are calculated to measure the extent of distraction. And then we select the largest distraction extent degree to estimate the engagement degree of the student. Finally, based on the deviation and the face emotion, the engagement degree can be computed.

4.1.1.1 Head pose estimation To robustly estimate the head pose orientation and improve the accuracy of the results, the method based on a regularized maximum likelihood Deformable Model Fitting (DMF) reported in Cai et al. (2010) which is robust against the impact of noise factors in the depth channel. As this method has been developed in the latest version v1409 of Kinect v2 Windows SDK, in our experiments we utilize the module directly to obtain the 3D head pose orientation of the student in E-learning environments. In our experiments, we use the latest model Kinect v2 as shown in Fig. 3a which is more robust than the previous model (Almohammadi et al. 2014). The SDK of Kinect v2 provides and describes head pose relating to the Kinect camera by three angles: pitch, roll, and yaw, as demonstrated in Fig. 3b.

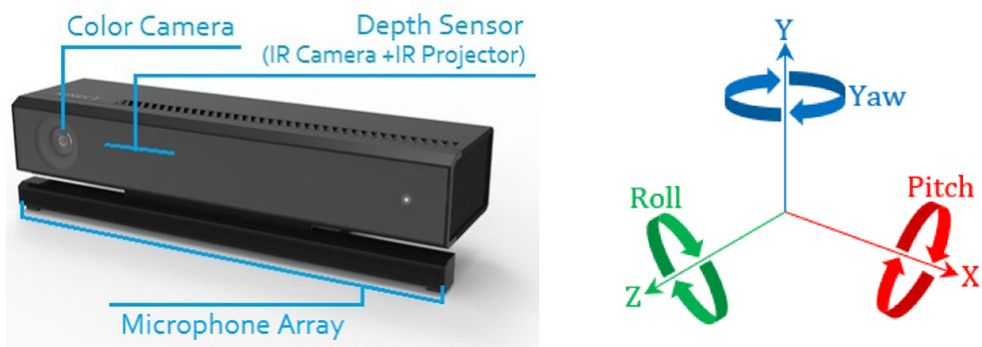
4.1.1.2 Engagement degree estimation Based on the visual features including head pose together with the face emotion returned by the 3D sensor, in our experiments, we will consider the following assumptions describing the relation between the input visual features and the output engagement degree:

- Facing the whiteboard (or computer screen in case of remote learning)—the student is engaged in the class.
- Facing down—the student is sleepy or probably playing a tablet/smartphone.
- Facing to the left/right—the user is distracted from the learning and interacting with another student nearby.
- Looking around/away—the student is thinking about irrelevant problems and is not concentrated.
- Face emotion—one eye is not open or both of the two eyes are closed (*falling-asleep*), and other face emotion for example, mouth open and close (*speaking*), facial expression is *happy*, face emotion is *engaged*, etc.

Based on the assumptions above, the engagement degree of the student can be calculated and modeled by the face emotion of the student and the deviation between the current head orientation and the optimum engaged head pose (facing towards the whiteboard) which are shown in the following equations.

$$\text{Engagement Degree} = (1 - \text{Deviation}) \times \text{Emotion Modifier}, \tag{3}$$

where Emotion Modifier is decided by the facial emotion including falling-asleep, speaking, happy, engaged. In this experiment we mainly consider the factor falling-asleep for



(a) **(b)**

Fig. 3 **a** The used Kinect v2. **b** Head pose angles

face expression analysis:

$$\text{Emotion Modifier} = \begin{cases} 1 & \text{Two eyes are open} \\ \text{OEC Modifier if} & \text{One eye is closed} \\ 0 & \text{Two eyes are closed} \end{cases}, \tag{4}$$

where OEC Modifier is in the range of 0 and 1, and can be determined by the actual application scenario.

$$\text{Deviation} = \max\{D_{\text{pitch}}, D_{\text{roll}}, D_{\text{yaw}}\} \tag{5}$$

$$D_{\text{pitch}} = \frac{|\text{Pitch}_c - \text{Pitch}_o|}{\text{Pitch}_{\max}} \tag{6}$$

$$D_{\text{roll}} = \frac{|\text{Roll}_c - \text{Roll}_o|}{\text{Roll}_{\max}} \tag{7}$$

$$D_{\text{yaw}} \frac{|\text{Yaw}_c - \text{Yaw}_o|}{\text{Yaw}_{\max}}, \tag{8}$$

where Pitch_c, Roll_c, Yaw_c are the three angles (pitch, roll, and yaw) of the current head pose obtained by the Kinect v2. Pitch_o, Roll_o, Yaw_o are the angles describing the optimum engaged head pose orientation which are recorded in the training stage. $\text{Pitch}_{\max}$, $\text{Roll}_{\max}$, $\text{Yaw}_{\max}$ are the maximum angles defined and returned by the Kinect v2 SDK.

4.2 Fuzzy logic component

4.2.1 Extracting the interval type-2 fuzzy sets

Classification of the acquired teaching–learning behavior input/output data through the relevant fuzzy membership functions is a vital step in this component layer. The raw input and output values are ultimately quantified through this process, which leads them into linguistic labels such as *low/moderate* and *high* for the average level of engagement. The type-2 fuzzy set extraction approach used is indicated in Liu et al. (2007), Almohammadi et al. (2014) and Almohammadi and Hagras (2013b), by which a type-2 fuzzy set is developed and its FOU embeds the numerous type-1 fuzzy sets, so that each teacher's individual interpretation can be specified regarding a particular linguistic label that justifies the appropriate instructional approach and various varied learners' average engagement levels. Therefore, the teachers' diverse views with regard to modeling these words would be integrated by the FOU produced, and the uncertainties would also be handled for the type-2 fuzzy sets. In this method, data are gathered by questioning the teachers regarding their specific linguistic labels through which type-1 fuzzy sets would be produced. Subsequent to this step, the type-2 fuzzy sets are produced, while the type-1 fuzzy sets (demonstrating the teachers' individual views) are integrated, through which the FOU of the type-2 fuzzy set is delivered to represent the given word. Through the application of the Representation Theorem (Mendel 2001; Liu et al. 2007), each of the interval type-2 fuzzy sets $\tilde{A}_s$ can be calculated as follows:

$$\tilde{A}_s = \bigcup_{i=1}^{n} A^i. \tag{9}$$

In this equation, $\cup$ is an aggregation operation and A^i is referred to as the ith embedded type-1 fuzzy set (Liu et al. 2007). Reckoning the upper MF $\overline{\mu}_{\tilde{A}}(x)$ and the lower MF $\underline{\mu}_{\tilde{A}}(x)$ of $\tilde{A}_s$ can deliver the process of $\tilde{A}$ production. The embedded type-1 fuzzy sets and the upcoming FOU model for $\tilde{A}_s$ would collectively decide the occurrence of this mechanism. For the upper and lower MF parameters, interior FOU models, right and left shoulder MFs (shown in Fig. 4a–c) are to be applied in our system. According to Fig. 4a, the parameters: $\underline{a}_{\text{MF}}$, $\underline{c}_{\text{MF}}$, $\bar{c}_{\text{MF}}$, and $\overline{b}_{\text{MF}}$ denoting a trapezoidal upper MF and the parameters: $\bar{a}_{\text{MF}}$ and $\underline{b}_{\text{MF}}$ for a symmetric triangular lower MF, with an intersection point (p, μ_p) are most likely to describe the resulting interior interval type-2 fuzzy set (Liu et al. 2007). We describe below the procedures for calculating these parameters:

The type-1 MFs for each of the i teachers are described according to the parameters $[a^i_{\text{MF}}, b^i_{\text{MF}}]$. For interior FOUs,

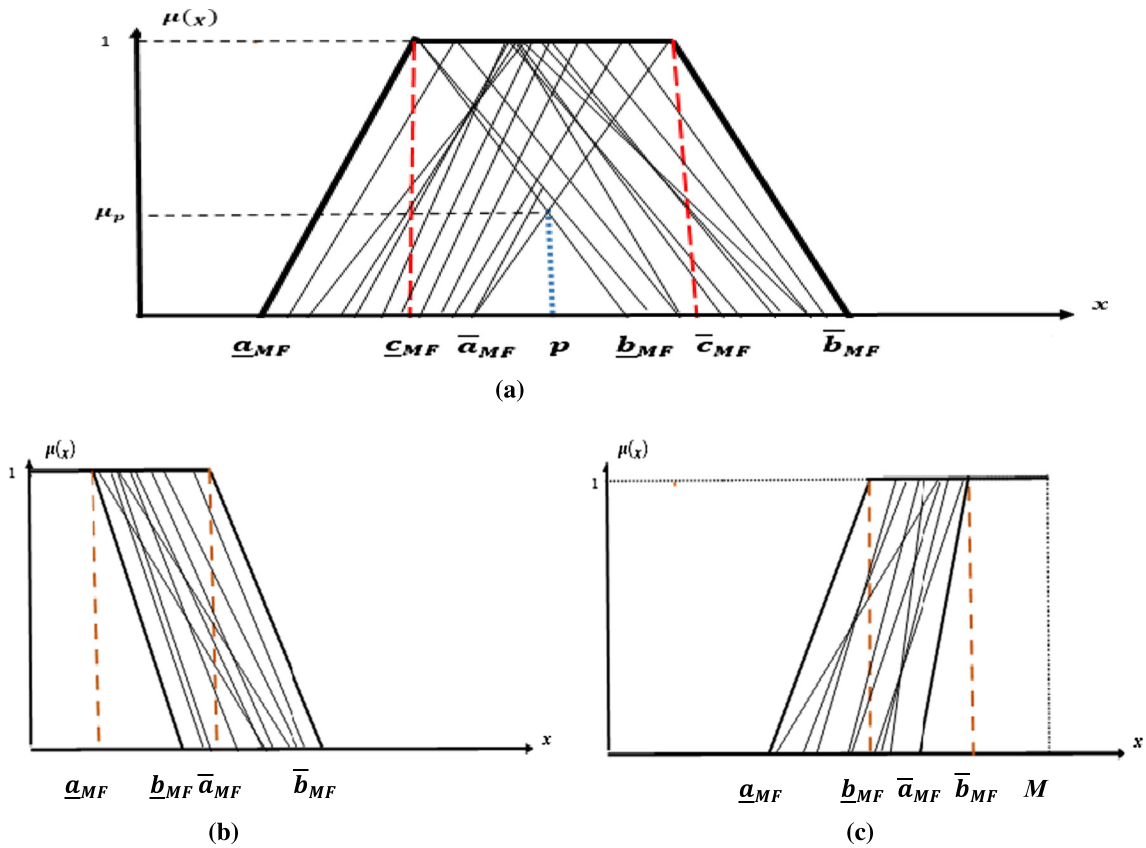


Fig. 4 **a** An interior type-2 MF embedding the different type-1 fuzzy sets, **b** *left* shoulder type-2 MF embedding the different type-1 fuzzy sets, **c** *right* shoulder type-2 MF embedding the different type-1 fuzzy sets (Liu et al. 2007)

we provide below the procedure for assessing the FOU model (Liu et al. 2007): We should follow the given steps for the upper MF $\overline{\mu}_{\tilde{A}}(x)$,

(1) For $\mu(x) = 0$, determine $\underline{a}_{\mathrm{MF}}$ to be equal to the minimum $a^{\min}_{\mathrm{MF}}$ of all left-end points a^{i}_{MF} and $\overline{b}_{\mathrm{MF}}$ to be equal to the maximum $b^{\max}_{\mathrm{MF}}$ of all right-end points b^{i}_{MF} (Liu et al. 2007).
(2) For $\mu(x) = 1$, calculate $\underline{c}_{\mathrm{MF}}$, $\overline{c}_{\mathrm{MF}}$ which correlate to the minimum and the maximum of the centers of the type-1 MFs.
(3) Approach the upper MF $\overline{\mu}_{\tilde{A}}(x)$ by joining the following points with straight lines: $(\underline{a}_{\mathrm{MF}}, 0)$, $(\underline{c}_{\mathrm{MF}}, 1)$, $(\overline{c}_{\mathrm{MF}}, 1)$, and $(\overline{b}_{\mathrm{MF}}, 0)$ Fig. 4a illustrates the result, which is a trapezoidal upper MF.

Following are the steps to estimate the lower MF $\underline{\mu}_{\tilde{A}}(x)$:

(1) For $\mu(x) = 0$, determine $\overline{a}_{\mathrm{MF}}$ to be equal to the maximum $a^{\max}_{\mathrm{MF}}$ of all left-end points a^{i}_{MF} and $\overline{b}_{\mathrm{MF}}$ to be equal to the minimum $b^{\min}_{\mathrm{MF}}$ of all right-end points b^{i}_{MF} (Liu et al. 2007).
(2) By using the following equations, compute the intersection point (p, μ_p) (Liu et al. 2007):

$$p = \frac{\underline{b}_{\mathrm{MF}}\left(\bar{c}_{\mathrm{MF}} - \bar{a}_{\mathrm{MF}}\right) + \bar{a}_{\mathrm{MF}}\left(\underline{b}_{\mathrm{MF}} - \underline{c}_{\mathrm{MF}}\right)}{\left(\bar{c}_{\mathrm{MF}} - \bar{a}_{\mathrm{MF}}\right) + \left(\underline{b}_{\mathrm{MF}} - \underline{c}_{\mathrm{MF}}\right)} \tag{10}$$

$$\mu_p = \frac{\left(\underline{b}_{\mathrm{MF}} - p\right)}{\left(\underline{b}_{\mathrm{MF}} - \underline{c}_{\mathrm{MF}}\right)}. \tag{11}$$

(3) Approximating the lower MF $\underline{\mu}_{\tilde{A}_s}(x)$ by joining the following points with straight lines : $(\underline{a}_{\mathrm{MF}}, 0)$, $(\overline{a}_{\mathrm{MF}}, 0)$, (p, μ_p), $(\underline{b}_{\mathrm{MF}}, 0)$, and $(\overline{b}_{\mathrm{MF}}, 0)$. The result according to Fig. 4a is a triangle lower MF.

The method adopted for computing the FOU for the right and left shoulder is similar to that described in Liu et al. (2007). To compute the upper MF $\overline{\mu}_{\tilde{A}}(x)$ for the left shoulder (as shown in Fig. 4b), points $(0, 1)$, $(\overline{a}_{\mathrm{MF}}, 1)$ and $(\overline{b}_{\mathrm{MF},0})$ should be joined with straight lines. To compute the lower MF $\underline{\mu}_{\tilde{A}}(x)$, points $(0, 1)$, $(\underline{a}_{\mathrm{MF}}, 1)$, $(\underline{b}_{\mathrm{MF}}, 0)$, and $(\overline{b}_{\mathrm{MF}}, 0)$ should be connected with straight lines. Similarly, as shown in Fig. 4c), to estimate MF $\overline{\mu}_{\tilde{A}}(x)$ for the right shoulder, points $(\underline{a}_{\mathrm{MF}}, 0)$, $(\underline{b}_{\mathrm{MF}}, 1)$, and $(M, 1)$ should be joined with straight lines. To approximate the lower MF $\underline{\mu}_{\tilde{A}}(x)$, points

$(\underline{a}_{\mathrm{MF}}, 0)$, $(\overline{a}_{\mathrm{MF}}, 0)$, $(\overline{b}_{\mathrm{MF}}, 1)$, and $(M, 1)$ should be joined with straight lines (Liu et al. 2007).

4.2.2 Extracting the fuzzy rule from the collected data

The data collected from the e-learning environment (input/output) are combined with the extracted type-2 fuzzy sets so that the rules describing the actions of teachers can be extracted. An enhanced form of the Wang–Mendel technique is used to drive the rule extraction method employed in this paper (Wang 2003; Hagras et al. 2007). This is a one-pass technique for extracting fuzzy rules from the accumulated data. The fuzzy sets for the antecedents and consequents of the rules divide the input and output space into fuzzy regions. Several multi-input/multi-output rules are extracted using the type-2 fuzzy system, through which the association between $x = (x_1, \ldots, x_n)^T$ and $y = (y_1, \ldots, y_k)^T$ can be explained:

$$\text{IF } x_1 \text{ is } \tilde{A}_1^l \ldots \text{ and } x_n \text{ is } \tilde{A}_n^l \text{ THEN } y_1 \text{ is } \tilde{B}_1^l \tag{12}$$

$l = 1, 2, \ldots, M$, where l is the index of the rules and M is the total number of rules.

Specifically, for each input x_s where $s = 1, 2, \ldots, n$, there are V_i interval type-2 fuzzy sets $\tilde{A}_s^q, q = 1, \ldots, V_i$. Moreover, for each output y_c, there are V_o interval type-2 fuzzy sets $\tilde{B}_c^h, h = 1, \ldots, V_o$, where $c = 1, 2, \ldots, k$.

To clarify and summarize the following representation, an approach comprising a single output is illustrated because of the simplicity of the method for upgrading the rules involving multiple outputs. We mention below the several stages included in this rule extraction.

Phase 1 The upper and lower membership values are calculated $\bar{\mu}_{\tilde{A}_s^q}(x_s^{(t)})$ and $\underline{\mu}_{\tilde{A}_s^q}(x_s^{(t)})$ for each of the fuzzy sets $\tilde{A}_s^q, q = 1, \ldots, V_i$, and for each input variable $s(s = 1, \ldots, n)$ regarding a fixed input–output pair, $(x^{(t)}; y^{(t)})$ in the dataset $(t = 1, 2, \ldots N)$. Find $q* \in \{1, \ldots, V_i\}$ such that (Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013a):

$$\mu^{cg}_{\tilde{A}_s^{q*}}(x_s^{(t)}) \geq \mu^{cg}_{\tilde{A}_s^q}(x_s^{(t)}) \tag{13}$$

for all $q = 1, \ldots, V_i$, where $\mu^{cg}_{\tilde{A}_s^q}(x_s^{(t)})$ is the center of gravity of the interval membership of $\tilde{A}_s^q$ at $x_s^{(t)}$, which can be calculated below (Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013a):

$$\mu^{cg}_{\tilde{A}_s^q}\left(x_s^{(t)}\right) = \frac{1}{2}\left[\bar{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right) + \underline{\mu}_{\tilde{A}_s^q}\left(x_s^{(t)}\right)\right]. \tag{14}$$

The rule given below is the rule generated by $(x^{(t)}; y^{(t)})$ (Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013a):

$$\text{IF } x_1 \text{ is } \tilde{A}_1^{q^{*(t)}} \ldots \text{ and } x_n \text{ is } \tilde{A}_n^{q^{*(t)}} \text{ THEN } y \text{ is centered at } y^{(t)}. \tag{15}$$

For all of the input variables x_s, there are V_i type-2 fuzzy sets $\tilde{A}_s^q$, which makes the greater amount of possible rules equal to V_i^n. However, when considering the dataset, there will be the generation of those rules amongst the V_i^n possibilities that show a dominant region comprising a minimum of one data point.

In the first phase, there is the generation of one rule for each particular input/output data pair, with the fuzzy set selected being that which is seen to obtain the greatest value of membership at the data point, and particularly selected as the one in the rule's IF element. However, this is not the final version of the rule, which will be computed in the following step. The calculation of the rule weight is accomplished as follows (Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013a):

$$wi^{(t)} = \prod_{s=1}^{n} \mu^{cg}_{\tilde{A}_s^q}(x_s(t)). \tag{16}$$

A rule $wi^{(t)}$ weight is a degree of the strength of the points $x^{(t)}$ regarding the fuzzy region covered by the entire rule.

Phase 2 For all of the data points from 1 to N, the first phase is repeated. With the help of this practice, N rules extracted from the data are taken in the form of Eq. (15). Phase 1 witnesses the generation of multiple rules, all of which have the same IF part in common but which are all conflicting. During this phase, those rules that have the same IF part are amalgamated to form a single rule. Subsequently, the rules N are divided into groups, with rules in each of the groups seen to have the same IF part. If it is considered that such groups amount to M, and it may also be stated that the group has N_l rules, therefore (Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013a):

$$\text{IF } x_1 \text{ is } \tilde{A}_1^l \ldots \text{ and } x_n \text{ is } \tilde{A}_n^l \text{ THEN } y \text{ is centered at } y^{(t_u^l)}. \tag{17}$$

where $u = 1, \ldots, N$ and t_u^l are the data points index of Group l. The equation given below shows how to calculate the weighted average of all rules involved in the conflict group:

$$av^{(l)} = \frac{\sum_{u=1}^{N_l} y^{(t_u^l)} wi^{(t_u^l)}}{\sum_{u=1}^{N_l} wi^{(t_u^l)}}. \tag{18}$$

Subsequently, a single rule is formed by integrating these N_l rules, resulting in the following form (Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013a):

$$\text{IF } x_1 \text{ is } \tilde{A}_1^l \ldots \text{ and } x_n \text{ is } \tilde{A}_n^l \text{ THEN } y \text{ is } \tilde{B}^l. \tag{19}$$

Fig. 5 An example of one of the extracted fuzzy rules

IF **the learners' average level of engagements** *is* **Low** *AND* the **learners' average standard deviation level of engagements** *is* **Moderate** *AND* **the difficulty level of the current lesson** *is* **Hard** THEN **the recommendation to use the "asking questions" teaching approach** *is* **High** *AND* **the recommendation to use the "practical explanation (demo)" approach** *is* **Low** *AND* **the recommendation to use the "teaching with cases (problem solving)" approach** *is* **Moderate** ***AND*** **the recommendation to use the "PowerPoint slides" teaching approach** *is* **Low**

where there is the selection of the output fuzzy set $\tilde{B}^l$ on the basis of the following: amongst the V_o output interval type-2 fuzzy sets $\tilde{B}^l, \ldots, \tilde{B}^{V_o}$ calculate the B^{h*} such that (Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013a):

$$\mu^{cg}_{\tilde{B}^{h*}}(av^{(l)}) \geq \mu^{cg}_{\tilde{B}^h}(av^{(l)}) \tag{20}$$

for $h = 1, 2 \ldots, V_o$.

$\tilde{B}^l$, is chosen due to the B^{h*}, where $\mu^{cg}_{\tilde{B}^h}$ is the center of gravity of the interval membership of $\tilde{B}^h$ at $av^{(l)}$ as illustrated in Eq. (14).

The proposed system can effectively handle the data pairs of input/output, including multiple outputs as per the work presented above. Stage 1 is recognized as being distinct with regard to the number of outputs associated with each rule. By contrast, Stage 2 provides a straightforward expansion with the aim of enabling rules to encompass multiple outputs; for each output, the calculations detailed in Eqs. (18–20) are repeated. An example of the extracted rule with multiple inputs–outputs is shown in Fig. 5.

4.3 The IT2FLS and adaption component

The generated type-2 fuzzy sets and the fuzzy rules extracted from the input and output gathered data of learners enables the proposed system to learn and obtain the best instructional approaches in accordance to the varied level of engagement of the learners and the difficulty level of the taught content. The system is consequently able to notify the teachers to re-adjust the online learning environment with specific consideration to appropriate instructional approach. The system actions are triggered through the examination and monitoring of various learners' varied levels of engagement and the lesson difficulty, which subsequently affects the online instructional environment, with a particular consideration of the learned approximation of best tutorial actions that could be followed by the teachers. The following are the functionalities of the proposed type-2 fuzzy adaptive system:

- As specified in the e-learning environment, the crisp inputs including the learners' variables are fuzzified (via singleton fuzzification) into the input interval type-2 fuzzy sets.
- The outputs (instructional approaches) type-2 fuzzy sets are generated by the activation of inference engine and rule base.

The proposed system must have the ability to be fine-tuned with respect to the dynamic and diverse varied learners' engagements and various difficulties of the taught lessons' states by continuously enabling teachers to modify their instructional approaches. Subsequently, the system will re-adjust its procedures or it would apply new ones. If no rules arouse from the rule base [i.e., the rule's firing strength in Eq. (16) $wi^{(t)} = 0$] in a given input, subsequently the system input would be captured by the system. To create a rule covering this uncovered input status, it will capture the appropriated teaching approaches. Therefore, new rules would be integrated in the system while there is an undefined state of the online learning environment at that moment as per the existing rules in the rules base (i.e., where none of the present rules are fired). The new rules will be generated and the system integrates them in such an instance, in which the online learning environment's current input states are specified by the antecedents besides the consequent fuzzy sets that are dependent on the current state of the instructional approach. The fuzzy sets that have membership values, where $\mu^{cg}_{\tilde{A}^h_c}(x_s^{(t')}) > 0$ are identified for all of the input parameters x_s. Consequently, for each input parameter, numerous identified fuzzy set(s) are generated in the form of a grid from which new rules are generated based on all individual combinations of successive input fuzzy sets. The consequent fuzzy set that provides the greatest value of membership to the teacher defines the appropriate instructional approach (y_c) so that it can operate as the generated rule consequent. After performing a calculation of the output interval memberships' center of gravity, we can establish the fuzzy sets (Wang 2003; Hagras et al. 2007; Almohammadi and Hagras 2013a):

$$\mu^{cg}_{\tilde{B}^{h*}_c}(y_c) \geq \mu^{cg}_{\tilde{B}^h_c}(y_c). \tag{21}$$

For $h = 1, \ldots, W$ the $\tilde{B}_c$ is chosen as $\tilde{B}^{h^*}_c$, where $c = 1, \ldots, k$. Consequently, new and upcoming rules can be progressively added.

In case the teacher needs to change the suited instructional approaches at a given input status, the fired rules will be identified and the rule consequents will be changed (if more than two teachers signal the same modifications for the teaching approaches), as indicated by Eq. (21). Therefore, the fired rules are modified so that the updated suited instruction approaches for the students could be reflected in a desirable way, while taking into account the existing state of the online learning environment. The system proposed in this paper adopts life-long learning through facilitating the adaptation of rules according to the optimized instruction delivery approaches by teachers, which notably change over time based on students varying levels of engagements and in regard to the state of the online learning environment. Owing to the system flexibility, the fuzzy logic model learned initially may be effortlessly expanded in order to make changes to both new and existing rules. These fuzzy rules enable a large range of values for all parameters (input and output) to be captured, which in turn enables the continuation of the generation of rules, even when the online learning environment gradually changes. On the other hand, if notable changes occur in terms of the students' varied average level of engagements or in the environment (which may not be captured by the present rules, as highlighted above), the new rules will be automatically generated, which ultimately satisfy present conditions. Accordingly, the inconspicuous system will expand its actions and may be adapted in order to improve the instruction delivery.

5 Experiment and results

Various real-world experiments were performed in the iClassroom of the University of Essex to compare the effectiveness of the proposed Interval Type-2 Fuzzy Logic based System (IT2FLS) with the Type-1 Fuzzy Logic based counterpart system (T1FLS) and the non-adaptive version of the system in regards of enhancing the quality of instruction to promote better student engagement and satisfaction. To perform the experiments, 20 lessons from a Microsoft Excel course were selected and categorized according to level of difficulty (i.e., very hard, hard, moderate, easy, and very easy). Furthermore, we examined four teaching approaches, namely teaching: using PowerPoint slides, practical explanation (demo), teaching with cases (problem solving), and asking questions. These approaches were recommended by different expert teachers to be used in the systems.

Real-world experiments were conducted with a sample of 30 students and six teachers from the University of Essex. The experiments began by training the system. Three groups were formed from the 15 students, each of which was randomly assigned five distance learners. An expert teacher was assigned to each group to teach 20 lessons using the four teaching approaches.

During the teaching sessions, the learners' average level of engagements and the average standard deviation level were measured and accumulated every five seconds, as well as the difficulty level of the current lesson being presented in the teacher–user interface; both were used as input variables. When the teacher decided to change the teaching approach, he/she should rank and prioritize these teaching approaches from zero (not beneficial in the current situation) to ten (absolutely beneficial in the current situation); this ranking was used as the output. The teacher recorded the inputs and their related outputs in the system's database. These inputs/outputs were captured by the observer component whenever the teacher changed or recorded the appropriated instructional approach. The left-hand side of Fig. 6. shows the teachers teaching the lessons while the right-hand side shows the students' engagement degree recognized by the teacher–user interface. The average engagement degree for each student was measured using the Kinect camera (as shown in Fig. 6 and as explained in Sect. 4.1.1).

It should be noted that the calculation of the average learners' engagement and the standard deviation was taken from the beginning of teaching a lesson in one of the four teaching approaches until teaching another lesson that differed in difficulty level or until changing the teaching approach.

After collecting sufficient datasets, we started the testing phase. Here, three five-member groups were taught by three different teachers (i.e., one teacher assigned to each group). The teacher in the first group used a system applying T1FLS, while the second group's teacher used applied IT2FLs recommendations. The third group did not use any technological system and served as the control group for the experiment. After dividing the three groups equally and the input and output data for type-1 and type-2 groups were obtained. Then, by using the linguistic variables and rules, the fuzzy logic models for both the type-1 and type-2 were constructed. The type-2 fuzzy sets (shown in thick line in Fig. 7) were obtained to capture the uncertainty that represents teachers' views regarding a particular linguistic label explaining the average of students' engagement, their standard deviation, and the teaching approach, while the type-1 fuzzy logic system uses a type-1 fuzzy set (shown in dashed lines) as it shown in Fig. 7. During the training phase, the total number of the extracted rules from the T1FLS were 13 and 10 for the T2FLS for each system single output. The addition or editing for existing rules were explained in Sect. 4.3. In addition, examples of the generated rule is shown in Fig. 5.

As soon as the teachers in the first and second groups started introducing the first lesson, the observer component started calculating the average engagement and the standard deviation. Simultaneously, the observer component tried finding the matched rule(s) with the current monitored inputs.

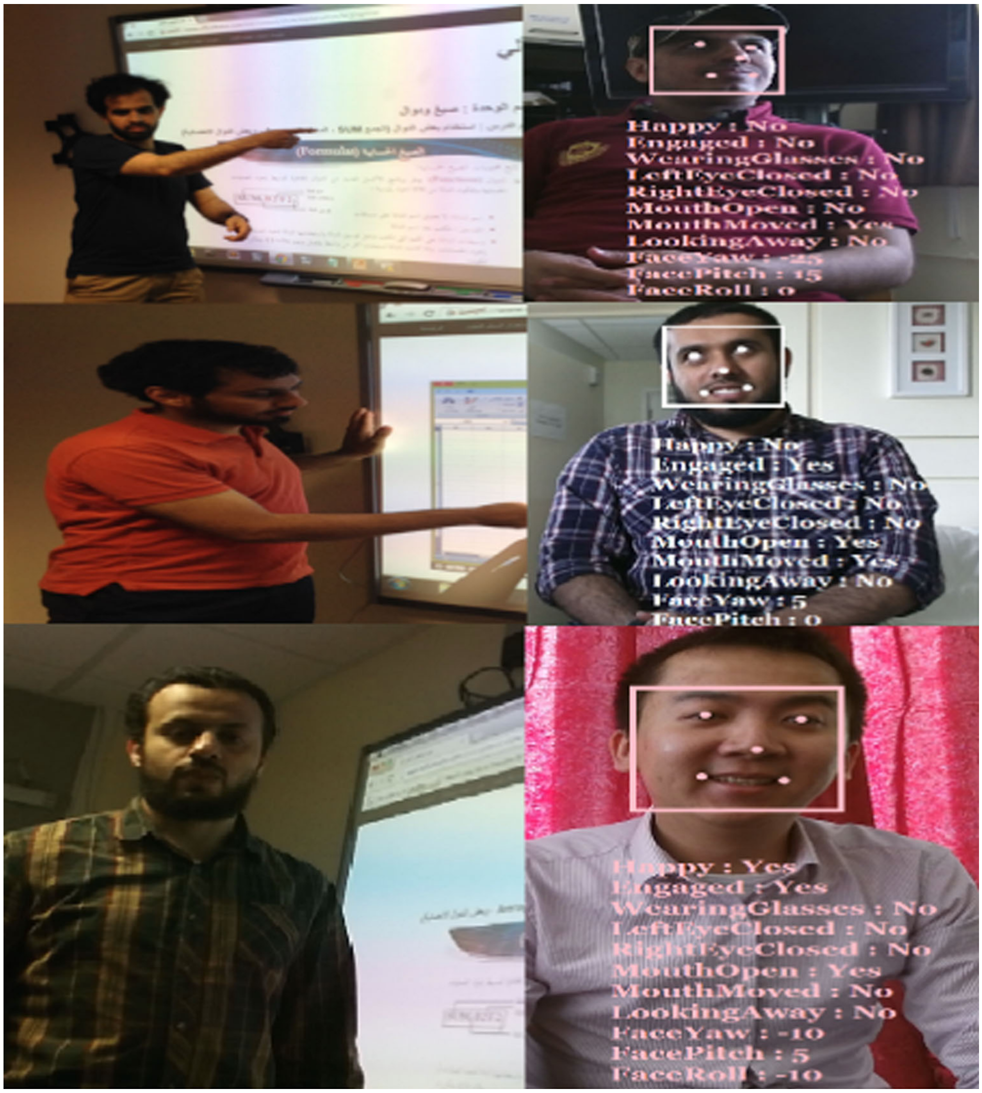


Fig. 6 Teachers are shown on the *left side* photographs while they are teaching different lessons with different teaching approaches. On the *right side* photographs, the students' engagement feedback are shown in the teachers' user interface

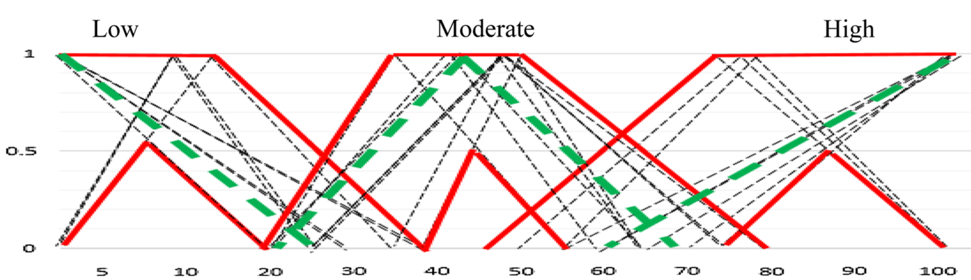


Fig. 7 The generated interval type-2 fuzzy sets of the average engagement level (*think solid lines*) and the type-1 fuzzy sets (*thick dashed lines*)

When the system found the matched rule(s), it would be presented in the teacher–user interface thus, he/she could know what the best teaching approach in that situation was given the output of the IT2FLS. The teacher could ignore this output and the system would learn from his/her decision of re-prioritizing and re-ranking the teaching approaches based on the current given data. Hence, if the teacher determined to continue teaching the lesson (or any lesson in the same difficulty level) without changing the teaching approach, the observer component will continue calculating the average engagement and the standard deviation. In contrast, if the teacher changed the teaching approach or taught a lesson

Table 1 Average error and standard deviation of the system outputs

Output name	Type-2 fuzzy logic		Type-1 fuzzy logic	
	Average error	Standard deviation	Average error	Standard deviation
Asking questions approach	2.60	1.43	2.73	1.88
Practical explanation (demo) approach	1.90	1.28	2.78	1.67
teaching with cases (problem solving) approach	2.09	1.32	2.88	1.79

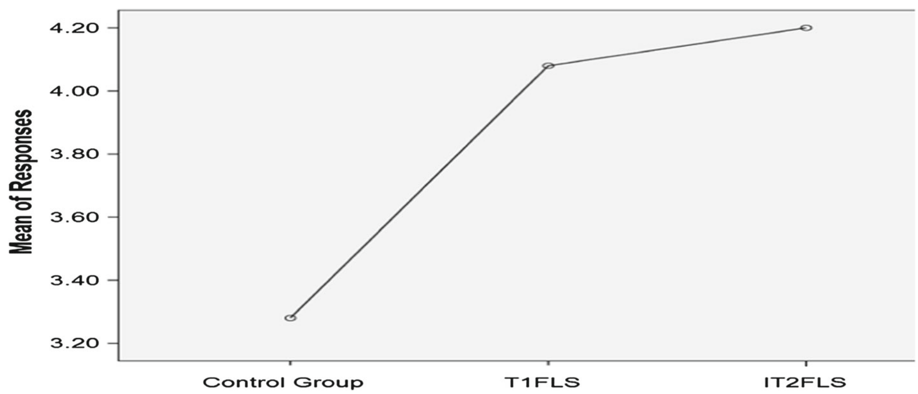


Fig. 8 Plot for group means comparison using Tukey

that differed from the previous one, the observer component would modify its action accordingly and adapt the corresponding rules.

The notification frequency is determined by changes in the monitored inputs (the e-learning environment state), modified by the average level of engagement, the average standard deviation of learners engagements, or the difficulty level of the lesson. We have noticed that these inputs do not sharply change, so the notifications should not affect the instructor mode of teaching. Through the experiments, it has been shown that 66 % of the suggested teaching approaches were followed by the teacher, whereas 34 % divided between the edited ones and the recommendation that affects the instructor mode of teaching. It is important to note that teachers might need some time to switch from one teaching approach to another, so they might in some cases ignore the recommended approach.

Finally, for evaluation purposes the teacher-learned data were collected to compare the type-2 and type-1 fuzzy logic system to know the average error and standard deviation of the teachers' preferred output and the system outputs. In addition, the comparison between the three groups in terms of the average engagements and standard deviations involved comparing them based on the data gathered by the observer component (during the whole teaching session for every group) and based on the students' views which tracked by their questionnaire responses.

Firstly, based on the teachers' learned data, Table 1. shows the average error and standard deviation to compare the teacher preferred output and the system outputs in both systems IT2FLS and T1FLS. These results clearly show that IT2FLS has less average error and standard deviation. Even for the least improvements in the "Asking questions Approach," the IT2FLS produced almost 5 % better performance when compared to T1FLS in terms of lower average error between the system output "asking question approach" and the preferred teacher-learned output "asking question approach." In addition, the IT2FLS produced better spread of the errors by having 23 % less standard deviation when compared to T1FLS. Consequently, IT2FLS appears to bemore effective than type-1 fuzzy logic system in recording teachers' tutorial actions.

On the other hand, according to data gathered by the observer component, the results indicated that the use of IT2FLS makes students more engaged and brings them closer to each other in terms of their degree of engagement. Accordingly, there was little dispersion of the set of engagement data for the IT2FLS group, with an average engagement degree of 68.75 and 10 % average standard deviation, compared to an average engagement degree of 64.23 and 16 % average standard deviation for the type-1 fuzzy logic system (T1FLS)—and a 44.34 % average engagement degree and 20 % average standard deviation for the control group.

Furthermore, we analyzed the participants' satisfactions in the questionnaire using ANOVA to compare the responses from the groups at a significance level of 0.05. The analysis revealed that there is a significant statistical difference between the various groups ($p \ll 0.05$). We also carried out Tukey comparison test to see which pair of groups has the difference. We observed that Group 3 (IT2FLS) and Group 1 (control group) were the most significantly different groups as compared to other pairings, as shown in Fig. 8.

6 Conclusions and future work

This paper presented an interval type-2 fuzzy logic-based system that can learn different teacher's pedagogical decisions based on the content difficulty level as well as the students' average level of engagements and the variation between the engagements in a dynamic real online teaching environment. This learnt type-2 fuzzy-based model was applied to enhance the teaching performance by informing the teacher about the best teaching approaches in order to gain an enhanced average level learners' engagement.

Furthermore, we presented a method based on type-2 fuzzy logic utilizing visual RGB-D features including head pose direction and face expressions captured from a low-cost but robust 3D camera (Kinect v2) to measure the engagement degree of the students in both remote and on-site education.

The IT2FLS has been tested and compared with the T1FLS and with a non-adaptive system. The experiments were conducted with a population of six teachers and 30 students at Essex University. The results revealed that IT2FLS was better able to handle uncertainties where IT2FLS produced lower average errors and standard deviation compared to T1FLS between the system outputs and the preferred teacher outputs. This has resulted in increasing the average level of engagement over the T1FLS group by 7 %; the engagement level improved over the control group by 55 %. Furthermore, the use of the IT2FLS system brought the students' engagement levels closer together, yielding an average standard deviation improvement of about 37.5 % over the T1FLS group and about 50 % over the control group. Using ANOVA and Tukey tests, we found that the satisfaction level of the participants in the IT2FLS differed significantly from the satisfaction level of students in the control group ($p < 0.05$).

Thus, these promising results from the proposed system has facilitated the instruction with better delivery to the learners more than the type 1 fuzzy systems and the non-adaptive version.

It should be noted that the proposed system can be scalable and is designed for a large number of remote students. In addition, the system can be extended in terms of the relations between more varied student input variables and more teaching methods outputs to be tested. In the future, we intend to carry experiments with large size classes.

In the future, we aim to employ general type-2 fuzzy logic to be able to better handle the model the various faced uncertainties. We also aim to deploy the proposed system for e-learning courses including thousands of students.

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