Teaching with a Dual-Channel Classroom Feedback System in the Digital Classroom Environment

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Abstract—Teaching with a classroom feedback system can benefit both teaching and learning practices of interactivity. In this paper, we propose a dual-channel classroom feedback system integrated with a back-end e-Learning system. The system consists of learning agents running on the students' computers and a teaching agent running on the instructor's computer. The learning agent collects both instructional and social responses from the students and then sends them back to the instructor's computer through a two-channel mechanism. The instructional responses are obtained by recognizing the spoken keywords; while the social responses are obtained by analyzing the social signals provided by students' head movements. Later, the teaching agent displays the summarized responses on the teaching dashboard for the instructor to evaluate their teaching practices. Empirical experiment results show that the system has an acceptable performance and provides enhanced interactivity in both learning and teaching. Also, further analysis reveals that the dual-channel mechanism not only provides the basic functions of a classroom feedback system, the student's responses to the instructor's questions, but also promotes both students and instructors to be engaged and attentive in class. As the two-channel feedback mechanism can be embedded into an e-Learning system, the proposed system is an enhancement of a digital classroom environment. In short, with the help of the two-channel feedback mechanism, interactivity on teaching practices and learning activities can be greatly improved. Students can then acquire a much better learning experience and satisfaction.

Index Terms—Classroom feedback systems, e-Learning tools, social and behavioral sciences, course management system

1 Introduction

Rapid receipt of feedback (or response) from students about their understanding during a lecture can help them learn more efficiently [1]. Traditionally, the student's response is obtained through assessment practices, such as surveys, homework, quizzes, and reports. Since such types of feedback are not instantly received during a lecture, the Classroom Feedback System (CFS), also known as the Classroom Response System (CRS), the Personal Response System (PRS), or the Student/Audience Response System (SRS/ARS), have been introduced to fulfill such a demand [2]. Typically, a CFS can effectively capture the learning responses during a lesson. Through the received feedback, the teacher may correspondingly change his/her teaching practices [3], [4].

A CFS can be implemented in various ways, such as a visual response system with double-sided and colour-coded flashcards for students, a computer system consisting of proprietary software installed in the instructor's computer to collect information sent from students' devices, or even wireless mobile devices designated for students to input their answers [5]. With the help of a CFS, students can have their feedback channel at any time. Consequently, collaboration and cooperation are enhanced among students [6].

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In higher education, however, it is very challenging to obtain students' responses during a lesson. For instance, a university lecture hall is often large enough to accommodate more than 100 students. In such a large class, students are often hesitant or unwilling to speak, as they are afraid of being embarrassed by making mistakes publicly, and consequently facing their peers' disapproval [7]. Without the feedback from students, the instructor may be forced to acquire it aggressively, such as calling for a volunteer, calling a name from a roll book, or assigning a different response group of students on a daily basis [7]. Hence, acquiring responses is tedious and time-consuming work, and even though a CFS can automatically collect the responses for the instructor, it is still doubtful as to whether the students are willing to give more feedback through the CFS.

Generally speaking, a student response may be explicit (e.g., a direct answer) or implicit (e.g., body language), but a conventional CFS only collects explicit, structured, and self-expressing short messages as the response. In practical situations, an implicit message is equally as important as the explicit one. Implicit messages can be expressed by head movements, facial expressions, body language, and so on. The implicit messages can be viewed as a kind of social interaction that happens during the teaching process. To address this phenomenon, we divided classroom feedback into two types: instructional feedback (explicit) and social feedback (implicit). In many studies, instructional feedback refers to a formal survey for teaching methods and practices that needs to be tweaked and improved. Here, however, we use this term to refer to the instant feedback with regard to the instructor's questions or activities. Namely, instructional feedback is a selection response that asks the students to select a reply from the provided alternatives in terms of the instructor's question.

Because the main function of a CFS is to transmit students' feedback, to broaden the interaction's baseline, an effective CFS should capture both the instructional (explicit) and social (implicit) feedback to reflect the students' responses completely. The more one understands how students are learning, the more effective one's teaching will be. By following this way of thinking, we propose a CFS with a dual-channel feedback mechanism, which not only automatically collects the instructional feedback from the students, but also analyses the implicit messages from their head movements. The analysis result and discussion based on laboratory experiments confirms the usability of the proposed system, the interactivity improvement on learning/teaching, and the pedagogical benefits.

This paper is organized as follows: Section 2 briefly overviews the development of the CFSs from the literature. Section 3 describes the features of the pedagogical interactivity on the CFS. Section 4 emphasizes the importance of the social signal facet in pedagogical interactivity. Section 5 explains the reason for adopting head movement detection in a CSF. Section 6 presents the design of the proposed system including the software/hardware architecture, system deployment, and classroom environment. Section 7 reports several experiments and discussions. Finally, Section 8 is the conclusion and discusses future work.

2 Overview of the Classroom Feedback System

Instructional technology for teaching assistance plays an increasingly important role in the digital classroom. This is in spite of the cumulative importance, as pointed out by Roach [8], of whether instructional technology should be based on sound and judicious planning. Among these instructive/assistive technologies, the CFS receives remarkable notice. Historically, an early CFS was deployed with the use of flashcards [9]. In that system, the instructor asks the students to respond promptly to the posed questions by showing double-sided, colour-coded cards. Later, a more advanced method was proposed by using clickers (handheld devices) for students to give feedback immediately for the posed questions. Then, the instructor might well adjust the teaching pace according to the received feedback. This dynamic response-dependent teaching method based on CFS reflects a student-oriented teaching concept [8].

When compared with the flashcards, Martyn [10] points out two distinct key features that the clickers have: 1) They provide a mechanism for students to participate anonymously; and 2) They integrate a gamer approach operation that may better attract students' attention than a traditional class discussion. Caldwell [7] confirms that the clicker system is especially valuable for monitoring the learning progress of individual students on lectures held in a large classroom. Huang et al. [9] showed that clickers are useful tools to improve the effectiveness of learning, especially for male students. Keough [11] reviews 66 clicker technology-based studies with a focus on the student perceptions/outcomes and indicates that the same perceptions/outcomes can be attained within the management discipline. Camacho-Miano and Campo [12] conclude that learning with clickers is effective, and a positive correlation is observed between students' grades and their willingness to use the clicker.

While a clicker is positioned as a lightweight feedback transmitter, some studies use a more complicated (heavyweight) feedback transmitter as a clicker for better integrating with a backend course support system. Thus, the entire system becomes an online classroom or e-Learning system [13], [14]. For example, a personal data assistant (PDA) can be used as a heavyweight clicker to assist students' learning with satisfaction [5], [15]. Besides using a PDA, a tablet may well serve the same role, as demonstrated by Razmov and Anderson [15]. The instructor poses a question written on a slide and displayed on a tablet in front of each student, and then the students write their answers in digital ink and then submit them to the instructor.

Currently, a CFS system combined with the e-Learning system in the backend may incorporate smart phones/tablets as the frontend. It is typical that the backend system can collect and analyze students' responses instantly with possibly a personalized analysis [16]. For instance, McLoone et al. [17] designed and evaluated a backend system using tablets as the frontend to collect students' responses during an engineering class. Siddiqi et al. [4] used an automated short-answer marking system to improve teaching and learning. In addition, Adam et al. [18] proposed a system consisting of a lecturer mobile application (program), a student mobile application, and an administration web environment for a lecturer. Halimi et al. [19] stated that an intelligent e-Learning system should better fit the needs of the users (i.e., the students), especially when considering their interests, preferences, motivations, objectives, and knowledge.

The way to extend the capability of a CFS is through the use of emerging technologies. Lin et al. [3] proposed a CFS with affective computing technology to analyze the learner's facial expressions. They pointed out that a learner's autonomy often impacts the learning effect. Namely, a traditional CFS may not be useful if learners are absent-minded, or do not pay attention, to provide a response to the CFS. Therefore, more advanced means to collect the feedback, such as their proposed facial expression analysis method, can be more useful for the diagnosis of the student's learning difficulties, and help the teachers to adjust their teaching practices. Barker and Gruning [20] presented findings that described various sources of student feedback that prompts the instructor to change their teaching practices. The various sources include formalized evaluations; feedback inferred from student performance; direct requests from students; and students' nonverbal behaviour [20].

The mapped education approach is an important aspect for the adoption of CFS. In the traditional didactic educational approach, instructors are in command of knowledge. Students dutifully absorb the knowledge provided by the instructors [21]. In this case, a CFS can constantly keep the instructor's authority and provide additional channels for students to engage in the teaching process subjectively.

Another key approach is the authentic education of constructivism, in that students are presented with practical problems or projects that have realistic purposes. Instructors

TABLE 1
Comparison of Classroom Feedback Systems

Approach	Students Side Device	Purpose/ Medium	Collecting/ Summary Tool
Flashcard CFS [9]	Flashcards	Instructional/ visual	Manual/ Sheet
Hand-held transmitter CFS [8]	Infrared transmitters, Clicker	Instructional/ IR, radio wave	Automatic/ Application
Mobile device CFS [18], [15], [4]	Tablet PC, Smart phone, Pad,	Instructional/ Network	Automatic/ Application
Online classroom [13], [14]	Networkable Computer	Social/ Network	Automatic/ Web
Affection detecting CFS [3]	Tablet PC, Smart phone, Pad,	Social/ Network	Automatic/ Application
Proposed CFS	AIO PC, Pad, Tablet PC, Smart phone	Instructional & Social/ Network	Automatic/ Web CMS[1] Dashboard

[1]*CMS stands for Course Management System.*

then give the designed learning opportunity to facilitate students in the ordinary practices and events of a group, which consequently allows the students to make connections between the school and the demands of their broader communities [22]. In this case, CFS enhances authentic learning by pushing students to give feedback periodically to their instructor, who then acts as a facilitator and uses the feedback to synchronize the progress of learning and teaching, especially when some students are experiencing difficulties of self-learning. Generally, student-centered pedagogy (e.g., authentic education), broadly related to constructivist theories of learning, is suitable for innovative methods of teaching, which promote students to participate in their own learning and foster transferable skills such as problem-solving, critical thinking, and reflective thinking [23].

The third noted approach is transformative education. The teacher is a designer of pedagogy, and the learner is a co-designer of education. Learning is a variety of knowledge processes, acts of knowing, or epistemological 'takes', of which there are no physical boundaries, life-wide, and lifelong [24]. Obviously, traditional CFS cannot fit the unlimited freedom of transformative education as the classroom has been extended into any entity. If we consider the eLearning system as a coordinator for CFS, an eLearning system with cloud service technology might partially support the interactivity that takes place in the unconstrained classroom.

To summarize, without regard to extreme conditions, a CFS can basically provide an additional dimension of interactivity, and then can enhance the interactivity between instructors and students [25]. Based on this concept, we have proposed our CFS solution with an implicit social feedback mechanism. Thus, combined with a traditionally instructional feedback mechanism on a CFS, the proposed solution can collect "dual-channel" feedback from the students. Because our system is deployed in the centralized control digital classroom, the traditional didactic education approach is much more suitable for our system.

For the complete comparison, brief descriptions of various CFS systems related to the proposed system are summarized in Table 1. Within the various CFS systems, the affection detection CFS is the one that is most similar to our proposed system in adopting affective computing technology. The affection detection CFS emphasizes the awareness of the student response when using a CFS for instructive purposes. Our proposed system, however, emphasizes the social interaction, which can be the second channel to reflect the student's social signal. In other words, student responses may include an explicit instructive response for a CFS question, and an implicit social response for social interaction. The two types of response are transmitted on different channels for students to interact with the instructor.

3 Interactivity of Classroom Feedback Systems

With respect to the pedagogical effects, a CFS can produce highly cited benefits on interactivity [25], [26], which is a critical element for teaching and learning in traditional classrooms [27]. When an instructor interacts more with students, they are much more likely to engage in learning. Likewise, instructors benefit from the interactive messages to assess whether there is a need to adjust the course materials or the pace of teaching. Interactivity is reflected in three key learning theories: behaviourist, cognitivist, and constructivist [25], [28], [29]. Behaviourists achieve the increased interactivity in the instructional design, which emphasizes the importance of feedback and student self-assessment in the learning process. Cognitivists focused on the effectiveness of interactivity, which transfers knowledge from instructors to students in different aspects, including questioning and answering, informative feedback, and explanations [25]. Constructivists otherwise emphasize the engagement of interactivity in which the students' attention can encourage them to organize pieces of information into a system of knowledge.

Siau et al. [25] tried to synthesize various definitions of pedagogical interactivity and classify them into five types of sources: 1) the active involvement of learners; 2) the patterns of communication among learners/instructors; 3) instructor–learner communication; 4) social, cooperative, or collaborative exchanges; and 5) a range of instructional activities and technologies. Moreover, the two most important characteristics of interactivity are communication and engagement.

With respect to the role, interactivity can be divided into individual interactivity from a student's viewpoint, and classroom interactivity from an instructor's viewpoint. The classroom interactivity is an overall average without considering the difference of individual interactivity, which might have a major variance from the average value. There also exist some limits of interactivity in a traditional classroom [25]: 1) The elasticity of class time: the available time is fixed and constrained; 2) Students' participation: for each student to answer the instructor's question is regulated as one at a time; 3) Students' motivation: students may be reluctant to express their opinions in front of the class due to the fear of embarrassment when expressing a wrong answer; and 4) the lack of teaching-learning synchronization mechanisms: instructors experience difficulty when assessing whether students are following the course activity and understanding the course materials in order to adjust the pace of teaching in real time.

Also, measuring a CFS on interactivity in the classroom is difficult, and most studies are either conceptual or merely reporting applications [30]. For this reason, Keng et al. [25] proposed 10 items to measure the construct of interactivity. Questionnaires designed for these 10 items are measured by a nine-point Likert scale with one representing "strongly disagree" and 9 representing "strongly agree." This research reveals that interactivity can be measured through 1) students' involvement in the class; 2) students' engagement in the class; 3) students' participation in the class; 4) students receiving feedback from instructors; and 5) students' self-assessment. When measuring, the interactivity before and after the implementation of the CFS was assessed in order to compare the difference.

4 The Social Facet of Interactivity

In a class discussion, the interaction between the instructor and students not only happens with a physical conversation, but also with nonverbal ones. A nonverbal conversation can be viewed as a type of social interaction where they communicate to each other with social signals. These are communicative and informative signals that imply social facts, such as social interaction, social emotions, social attitudes, and social relations [31]. Social signals are typically displayed by a series of nonverbal, behavioural cues including facial expressions, body postures, gestures, vocal outbursts, and so on. As identified by Rodrigues [32], the media of social signals consist of verbal or nonverbal conversational modality. In the classroom, we can also distinguish the interaction between the instructor and students into nonverbal and verbal modalities. For example, a student may say "Okay", or nod their head, to express a positive feeling or approval. Here, we refer to the verbal responses as "instructional signals" and the nonverbal responses as "social interaction signals" (or nonverbal social behaviour).

In the classroom, as the instructor can only see the front view of the students, the social signals the instructor can observe are limited to head movement, facial expression, and hand posture. Although a student's facial expression contains important social signals, it is difficult for the instructor to realize the details of the students' faces in just a few moments, especially in a large classroom. The same difficulty also exists in detecting the hand postures of all the students, as they may be blocked by front-seat students and/or other obstacles. Head movement, in contrast, is easier to detect because the movement is obvious from the instructor's viewing angle. However, it is also a non-trivial task for the instructor to observe the head movement of all the students simultaneously. Hence, without the assistance of a CFS, it is a challenging task for the instructor to receive the social signals displayed in a large classroom.

As pointed out by Heylen [33], typical social signals are backchannel signals, which is the feedback from the listener in the form of a head movement to correspond to the speaker's verbal or nonverbal request. For example, during a turn-taking activity, a participant repositions their head before the start of a talk to signal the adoption of a turn. Hence, the head movement reveals intuitive but important social signals, including nodding up and down, rotating horizontally left and right, tilting at the neck from side to side, and moving the head forward or backward. Actually, a head movement can have 14 different functions, such as to signal yes or no, to express interest or impatience, to enhance communicative attention, and so on [33]. That is, the head movement presents a variety of communication.

TABLE 2
The Social Signal of Head Movement

Head Movement	Functions	Social Signal
Nod downward	General indicator of emphasis	Agreement, Politeness
Nod upward	Indication of a "wider perspective"	Focus
Head forward	Indication of the need for "a closer look"	Interesting
Head backward	Emblem of being "taken aback"	Stress, Astonished
Head Shake	Indication of less favorable	Disagreement

Based on this discussion, we can realize that head movements play an important role for teaching/learning, as they contain neglected but valuable social signals that can largely improve pedagogical interactivity. If the instructor can make good use of social signals for classroom communication and engagement, we believe it would have an expectable impact for CFS development.

5 Pedagogical Applications of Head Movements

A larger challenge is that the interpretation of nonverbal behaviour may or may not be accurate [20]. Classroom nonverbal behaviour can be very different across cultures. For example, interpreting lack of eye contact from students as disengagement is not precise for the oriental culture, which avoids eye contact.

To confirm whether the meaning of a social signal based on the head movement fits the local culture (Taiwan) further, we conducted a brief survey to ask the opinions of 20 instructors from eight basic computer courses about their teaching experience on students' head movements. Most agreed that a head movement is easily observed during the lesson, and the head nodding downward and shaking are more representative and meaningful as the teacher can directly understand these signals as agreement and disagreement for their subject. This simple survey confirms the interpretation of the underlying social signals with the corresponding head movements in Table 2, are well-suited to our local culture.

In the proposed CFS system, we select the head movement as the main modality of social signal transmission since it is more easily observed from the viewing angle of the instructor, and can be imitated and replaced by a video capture device for the purpose of machine automation. We propose five types of head movement, whose social meanings are suitable for the representation of student response. Table 2 summarizes the movements and the corresponding meanings of the social signals [33], [34].

Although a head movement can transmit implicit social signals, the pedagogical application of using it in teaching/learning is another research topic. Instructors must control their teaching context to maximize the effect of utilizing a social signal in a given teaching situation. In other words, the practice to achieve pedagogical function through a social signal of a head movement is controlled by each instructor's empirical skill. Nevertheless, we exemplify and explain our major practical application as follows.

For the instructor, the first major practical application is to collect implicit classroom feedback from the students. The instructor views the head movement as a second channel of the student's response, which provides additional and informal information compared to the normal classroom response. When the instructor collects the student's response by normal feedback methods such as a flashcards, clickers, or mobile devices, the responses are interpreted as quantity-oriented but ignore the quality. If the responses are part of being absentminded or even ironic, the quality of feedback may not fit the instructional purpose. If the responses are accompanied by an abundant intensity of social signals, we may have more confidence in the quality of the student's feedback. For instance, if an instructor poses some questions for a student's response, widely accompanied by the increasing of head forward behaviour, may reveal the "interesting" signal. Thus, instructors may have more confidence in their collection of feedback and attest to their design of lesson delivery.

The second major practical application for an instructor is classroom assessment. In this case, head movement is only for instructional response purposes, and not with a social signal function. By using machine detection on head movement, we can simultaneously watch students in the same digital classroom. For example, selection response assessments that require students to select a response from the provided alternatives can be conducted with different meanings of a head movement. Nodding downward means agreement while head backward or shaking means something else. Likewise, supply response assessments that require students to supply or construct their own responses can be conducted with the voting expression of a head movement, in which students propose their open answers to the instructor made public in advance, and then their peers vote on these answers.

For students, the major practical application is to express their classroom feedback actively. Students are more willing to express opinions by body language because it is more natural. If students know that their instructor is using a system to watch their head movement, they could be more aggressive when giving feedback. For instance, students display a continuous head shake to express their "disagreement" signal, the instructor may realize that his/her current teaching activity is doubtful through the teaching dashboard, so that an adjustment of the following teaching pace is needed. Because the feedback process takes place instantly, it is more beneficial for a learning activity without any additional teaching instruction involved.

6 System Design

This section describes the design of the proposed system and the deployment environment. The deployed environment is a digital classroom suitable for developing the smart classroom and conducting the following experiments.

6.1 Dual-channel Feedback Mechanism

The core concept of system design is the mechanism of dual-channel feedback. The reason for the "dual-channel" drives from the consideration of pedagogical interactivity.

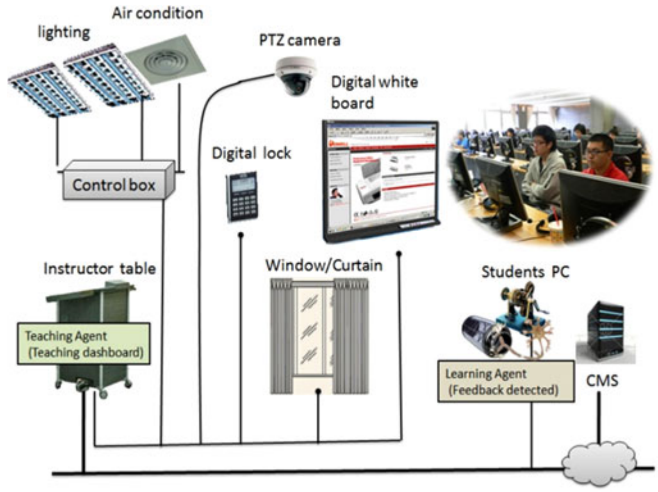

Fig. 1. Digital classroom environment with CFS.

Curriculum activity not only needs instructional interaction but social interaction That is, to broaden the baseline of interactivity, an innovative CFS should capture both instructional (explicit) and social (implicit) feedback to reflect student responses aggressively. In the classroom, instructional message can be explicitly transmitted between the instructor and students by traditional CFS, while an implicit social message needs a new channel to transmit. The new channel can be viewed as a kind of social interaction happening in the teaching/learning process. To address this phenomenon, we design the classroom feedback into two channels: instructional feedback (traditional) and social feedback (innovative).

To realize the instructional feedback channel, we do not use traditional clicker method, instead using voice recognition technology to detect the student's verbal answer. This design has some benefits. First, capturing a verbal response is more intuitive and ergonomic interface if voice input technology is mature. Students can instantly express their opinion by voice without device mediation. Secondly, the digital classroom environment allows us to introduce a new technological approach to simplify the deployment of devices if we can dismiss single-task devices such as traditional clickers. Thirdly, students do not need to learn how to operate the clicker device and can focus on the classroom interactivity. On the whole, the proposed system has two channels to receive two types of feedback message: instructional messages (verbal) and social signal messages (nonverbal).

6.2 Digital Classroom Environment

A digital classroom is a classroom equipped with an instructor station, which contains a computer and various device controllers. With the wired/wireless networks, the instructor station connects and/or controls the digital whiteboard, ceiling-mounted LCD projector and screen, surveillance cameras, multi-view LCD displayer, and audiovisual equipment, as shown in Fig. 1. For providing better services, the instructor station even in some digital classrooms can control lighting, air conditioning, windows/curtains, door lock, and energy-saving devices. Such a digital classroom environment integrates with automatic devices, controllable equipment, and network infrastructure and provides a further possibility of delivering intelligent learning systems.

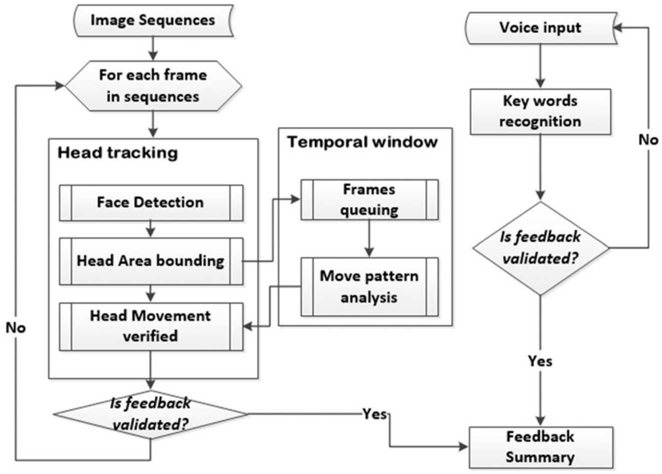

Fig. 2. Feedback processing flow of the learning agent.

The proposed feedback system is positioned to be deployed in a digital classroom. In front of each student is an AIO (all-in-one) computer with a built-in camera and microphone or a camera-equipped PC. On the instructor side is an instructor station containing a computer. The communication between the instructor and students is brokered by the teaching agent and learning agents. The teaching agent is installed on the computer of the instructor station for instructional control, whereas the learning agent is installed on the student's computer to capture voice and head movement. To simplify the work of installation, we construct a system website with the teaching agent. When the teaching agent is executed, the system website concurrently starts up to service. On its portal page, it has a download link for web installation of the learning agent. Thus, the deployment of the learning agents on students' computers becomes an easy task.

6.3 Learning Agent

The learning agent is designed to capture a student's two types of responses. To capture the implicit social response, the agent detects five types of head movement, including nod downward, nod upward, head forward, head backward and head shake. The learning agent also analyses the voice input answer, such as yes/no, left/right, number or alphabet character. The small set of keywords is predefined to the corresponding answer for the teacher's question. Since voice recognition technology is currently mature enough, we use the built-in library inside the operating system without expending extra programming effort. Conventionally, the speech recognition mechanism needs a training process for constructing individual voice profiles. In our case, a general-purpose profile is sufficient as the keyword set is small and the training need for each student customization can be ignored.

The flow of the learning agent to process student's response is shown in Fig. 2. We describe the steps as follows:

1. First, time-lapsed images are captured by the learning agent. The learning agent keeps image sequences in the memory buffer for further processing.
2. For each image frame in the sequences, the learning agent checks the head boundary from the face-blob-area detection.
3. The agent keeps tracking the moving of the head boundary in sequences to judge the pattern of head movement event in that moment.
4. If the head movement pattern is recognized as a validated feedback within the predefined temporal window, the agent sends an event notification to the teaching agent installed in the instructor-side computer.
5. The collected head movement events are summarized in the teaching dashboard.
6. The spoken keyword answer is also captured by the learning agent as the traditional clicker does. The recognized voice feedback is sent back to the teaching agent.
7. Finally, the teaching dashboard collects all students' both types of feedback and shows the summarized results for the teacher in a statistical manner.

6.4 Analysis of Head Movements

In the head-tracking module, we use the conventional tracking method based on the skin tone of the face. Specifically, the head-tracing module works as follows. For each video frame, down sampling is performed to reduce the computational burden of face detection as the tracking module is expected to execute in real time. Then, the skin-tone detector and the convex-region detector are applied to determine the head boundary. Also, the shoulder baseline is detected for head movement calibration. After finding the head area, the frame is cached in the temporal window. If the displacement of the head area in two successive frames does not exceed a threshold, only one frame is kept in the temporal window. The actual implementation of this module is based on a popular open-source library (Open CV) designed for real-time computer vision. The library supports the recognition of facial blobs in an image and uses them as the basis to detect the area of a human face.

In the temporal window, the last N frames are stored in receiving order. For each frame in the queue, the learning agent calculates the frame difference by subtracting pixel values in two consecutive frames (i.e., present and previous frames). The frame difference is copied into a new transparent layer in the image buffer. This operation is then repeated until all frame differences are calculated. The overlay of multiple transparent layers produces a dynamic moving pattern. Next, by calculating the horizontal and vertical projection histograms, we can infer the type of head actions.

Fig. 3 shows six basic head actions (we will address the relation between head action and head movement later). Each head action has its unique distribution on the horizontal and vertical projection histograms. The horizontal and vertical projection histograms can be combined to form a one-dimensional codec matrix. The learning agent uses the content of the matrix to classify the head action of the frames in the temporal window. For instance, the combination of a right-skewed distribution of vertical projection and a left-skewed distribution of horizontal projection means right-up head movement. Once a head action is determined, the cache of the temporal window is flushed, and the detection process can be started up again. Because the head movement is a composition of head actions, the agent uses the type of head actions and their temporal order to decide on the head movement. For

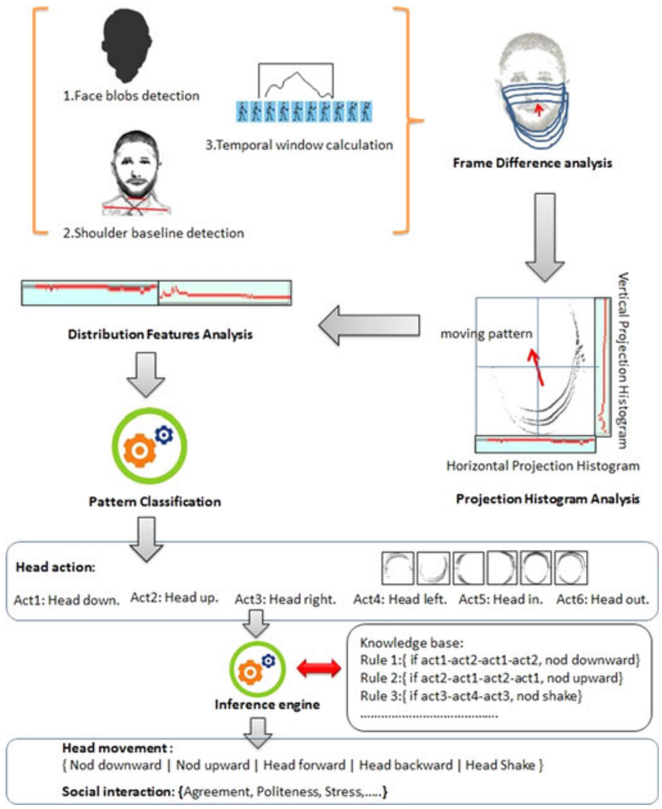

Fig. 3. Head movement detection.

example, we can define a set of head actions with a type of head movement as a classification rule. In terms of implementation, the decision mechanism is a rule-based classification tree, which is widely used in machine learning [35], with rules specified by a natural language.

After a head movement is determined, we can also calculate the relative confidence value of the classification. As a head movement consists of a series of head actions, we first compute the confidence value for each action. In a head action, the difference of the head locations between consecutive pictures is rather small compared to the size of the head. Thus, if more pixels are accumulated from the frame difference, the confidence of the action is higher. For a head action x, the confidence CF_x is calculated as:

$$CF_x = \frac{100 \cdot \sum_{i=1}^{N} \sum_{j=0}^{L-1} \sum_{k=0}^{W-1} |P_{i-1}(j,k) - P_i(j,k)|}{L \cdot W}, \quad (1)$$

where N is the number of frames in the temporal window, $P_i(j,k)$ is the image within the head boundary in the i-th frame in the window, and L and W are the length and width of the boundary box in the unit of pixels. After calculating the confidence value for each head action, the agent sums up the total value for all related head actions with a percentage value. The CF_x value then affects the transparency level of the student's icon on the teacher side's dashboard, as shown in Fig. 4.

6.5 Integration with E-Learning System

We use a popular open-source e-Learning portal, Moodle (Modular Object-Oriented Dynamic Learning Environment; also known as Course Management System) [36], as the backend e-Learning system integrated with the teaching agent. The portal supports a wide range of learning

Fig. 4. Teaching dashboard for social signal feedback.

activities such as courseware quizzes, chat, and multiple-choice activities.

With Moodle, the instructor can receive instant feedback through the web browser in the instructor's computer. Based on the programming model of Moodle, we develop a new activity module to capture the implicit feedback, called the "Feedback Surveillance Activity (FSA)" module. To use the module, the instructor follows the procedure that Moodle has specified to manage activity modules. For instance, the user selects a course, turns editing on, selects a topic or week, and then selects an activity (module) to add. Once the activity is selected from the dropdown menu, the editing mode of module is displayed. In the editing mode of the FSA module, the instructor can setup which types of head movement should be observed and adjust the channel parameters for the teaching agent and learning agents. After the parameters of feedback channels are setup, the system can begin to work for the instructor.

6.6 Teaching Agent and Dashboard for Feedback Summary

The teaching agent is designed to collect, analyze, and summarize student responses from the dual-channel feedback mechanism. The interface of the teaching agent is a teaching dashboard, as shown in Fig. 4. The teaching dashboard adopts a What You See Is What You Get (WYSIWYG)-style design. It provides basic attendance and seat management functions along with the courseware function.

To monitor the social signal feedback, the instructor can use the teaching dashboard to setup the social feedback function. There are five types of social signal feedback events in the selection menu of dashboard: Agreement, Focus, Interesting, Stress, and Disagreement. The instructor may, for example, select the Agreement item, and then the learning agent begins to detect the head movement during a specified time slot. When the head action has been judged as a head-nod event, the event message then is sent back to the teaching agent. Later, the teaching agent collects all the events from different students and presents the summary information on the teaching dashboard to the instructor.

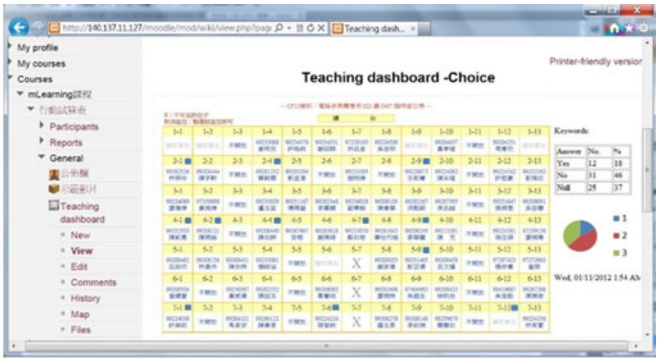

Fig. 5. Teaching dashboard for instructional feedback.

The teaching agent can also collect instructional feedback. As mentioned previously, the learning agent supports the recognition of spoken keyword answering. Such a capability allows students to answer the instructor's questions in the first place, as the traditional clicker does. For this application, the teaching agent displays statistical results of the collected answers, shown as Fig. 5. If necessary, the instructor may download the statistical data from the feedback summary page for formative assessment or further analysis.

7 Evaluation and Discussion

As the key concept of the proposed system is the dual-channel mechanism, the first experiment is to evaluate the performance of the dual-channel feedback and verify the practice and effectiveness of the system's design. This experiment has two aspects to be evaluated, including the instructional feedback channel and the social feedback channel.

In addition, we investigate the system's satisfaction through a questionnaire, to explore the empirical issues on pedagogical practices. The questionnaire is mainly designed to evaluate the system usability and the effectiveness of learning and teaching on a dual-channel feedback mechanism. Based on the results, we propose our pedagogical observations and discussion.

Finally, according to the questionnaire data, we try to analyze the correlation between the dual-channel feedback mechanism and pedagogical interactivity. First, we use the data transformation to convert the questionnaire into interactivity-related measurement data. Through statistical analysis, a regression model has been trained to verify the correlation between the proposed system and the related interactivity. By means of statistical evidence, the experimental result can be quantified and then presented.

The course selected for the experiments is "Introduction to computer science" taught by three instructors. They all have teaching experience of more than two years on basic computer courses. For each instructor's class, there are, on average, 68 students in the classroom. In the beginning of the semester, the students must learn how to use the learning agent and its associated hardware to answer questions given by the instructors. Students are divided into two groups for each classroom. The experimental group uses the proposed CFS system; the control group does not. Students are randomly (re-)assigned to either group for each week of the course. In the classroom, one group is seated on the left hand side, and the other group on the right hand side. The instructor can experience the differences when teaching both sides of the classroom. The whole experimental period for each course trial is eight weeks with a 2-hour lecture per week, and is held in a simulated digital classroom.

TABLE 3
Recognition Rate of Five Head Movements

Movement	Avg. True/Avg. Total	Avg. Recognition Rate
Nod downward	46/68	67.6%
Nod upward	43/68	63.2%
Head forward	35/68	51.4%
Head backward	36/68	53.0%
Head shake	51/68	75.0%

7.1 Performance Evaluation of Dual-Channel Feedback Mechanism

In this experiment, the first aspect is to evaluate the performance of the social feedback channel. The main measurement is to verify whether the system design on the recognition of head movement is effective or not.

For evaluating the recognition accuracy of each type of head movement, 10 students are randomly selected every week, and they are taught to act the five head movements listed in Table 2. The recognition results from the learning agents are compared with the actual head movement. The recognition rate is shown in Table 3, which shows that the head-nodding and head-shaking movements have higher recognition rates. The result coincides with the brief survey of local culture on the head movement mentioned in Section 5. That is, head-nodding and head-shaking are more representative and meaningful for the instructor to observe. This coincidence reveals that our algorithm design of head movement detection met with the human observation.

By contrast, the head-forward/backward movements are more difficult to recognize. As the frame difference contains fewer pixels in these two movements, the inference engine is difficult to interpret and consequently has a lower recognition rate. In the future, we plan to improve the recognition rate by adding more inference rules in the classification tree.

We found that some phenomena may confuse the system. For instance, when a student is drowsy in class, their head nodding may be a combination of head movement including nodding downward, moving forward, and head shaking, etc. In such a case, the proposed system is unable to detect the head movement correctly and infer the social signal. Another prevalent case is when the student is small and therefore hidden behind the student in front.

When the system fails to detect the head movement, the outcome means the overlooking of implicit messages from the students. In the real world, when the other side cannot detect the communicative signal, people often strengthen the intensity of expression and repeat it again until the other side obviously realizes it, or people choose to give up the expression directly as the urgency of interaction can be compromised at that moment. Hence, the missed detection of social signals may not be a problem because the interaction is for a social purpose with no immediate need. Also, students can repeat their expression again or even directly raise their hand. By contrast, the missed instructional feedback is more serious because collecting students' feedback is a purposeful step for an instructor to pose their questions. For verifying this situation, we conducted the second aspect of the evaluation.

TABLE 4
Experiment Setting

Group	Avg. No. of students	Treatment	Treatment effect
Experimental group	34	CFS	
VRG sub-group	17/34	Proposed CFS	See Fig. 6.
CRG sub-group	17/34	normal CFS	See Fig. 6.
Control group	34		

The second aspect is to evaluate the performance of the instructional feedback channel. Based on the same experimental setup, students in the experimental group are further divided into two sub-groups. The first sub-group uses voices to answer the questions (Voice Response Group, VRG) and the second sub-group uses clickers (Clicker Response Group, CRG), as shown in Table 4.

Because the instructional feedback channel plays the same role as the traditional clicker, we want to evaluate whether using voice recognition functions as well as the clicker. The main measurement is to compare the average response time when using voice recognition or a clicker. However, we might ask why we only selected the average response time instead of the execution rate of responding? When we push a clicker, the execution rate of responding is nearly 100 percent. However, the execution rate of responding on the voice recognition method depends on the recognition rate. Thus, a comparison based on the success of the execution rate is meaningless, as they are a different type of technology. Even if the feedback responding fails due to the voice responses not being captured correctly, students could try again, just as we use voice input on smartphones. The learning agent on the student-side computer will instigate a pop-up message to remind the student to voice their input again. The steps of the experiment are conducted as follows:

1. The instructor randomly (but equally) divides students in the experimental group into the mentioned two sub-groups 30 minutes prior to the end the class.
2. The instructor announces several questions displayed on the computer screens in front of students. The students are then asked to answer. There are three types of questions used in this experiment, including multiple-choice questions (type I), simple yes/no questions (type II), and fill-in-the-blank questions (type III), where students need to answer multiple keywords.
3. The VRG students state their answer directly into the microphones equipped on the student-side computers, while the CRG students click their answers with a mouse or keyboard. As the classroom is not equipped with real hand-held clickers, we use mice or keyboards to simulate the clicker system.

The average response time for both sub-groups is given in Fig. 6. In this paired histogram, the y-axis is the value of the average response time for the comparison of VRG and CRG. The x-axis concerns the question type, including multiple-choice (type I), yes/no questions (type II), and fill-in-the-blank questions (type III). It can be observed from Fig. 6 that the CRG students have a shorter response time than the VRG students for the first two types of questions (types I, II). However, for questions that require multiple-word answers (type III), VRG students have a shorter response time. It may be likely that the voice input is quicker than the typing input. With respect to this comparison, the difference in performance between the voice recognition and the clicker method is not obvious in terms of the students' adaptability. We can conclude that using voice recognition can function as well as the traditional clicker.

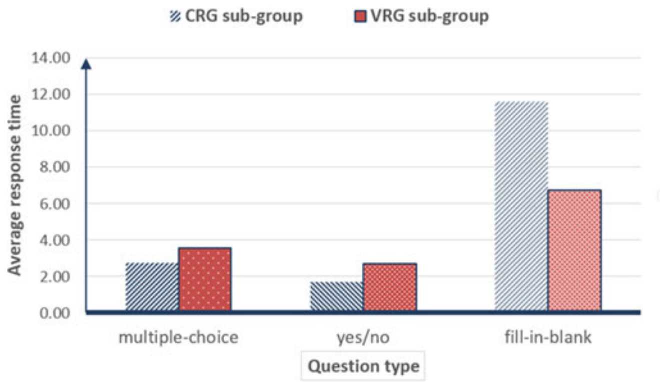

Fig. 6. Response time of various questions (in sec).

7.2 Survey of System Satisfaction

The questionnaire about satisfaction in usability is based on the format of the IBM Computer Usability Satisfaction Questionnaires [37], which emphasize psychometric evaluation and scenario-based usability evaluation. In our case, there are two designated scenarios for the usability evaluation:

1. Scenario one is for the survey of the instructional feedback channel, where the instructor wants to check the student's answer. Students are asked to answer the question by speaking the selected keywords. For a multiple-choice question, the keywords are numbered from 1 to 5. When the voice answer has been recognized, the system echoes with a beep sound and shows the recognized answer. If the shown answer is wrong, the student can speak again until answering correctly. After collecting the answers from all the students, the proposed system summarizes the results for the instructor.
2. Scenario two is for the survey of the social feedback channel. The instructor wants to know the current learning atmosphere or status (recall that the class is large) and uses the proposed system to view the summary of the collected social signals, which are displayed on the dashboard. Then, the instructor may adjust the teaching pace or practices to reflect the learning status. The collection of social feedback signals is operated in the background without interrupting the students' learning process.

For the purposes of comparison, a total of 60 questions are divided into four topic groups, including Social feedback, Instructional feedback by voice, Instructional feedback by clicker, and the integration of the proposed CFS system with the e-Learning system. The designated scenario for each topic group is one, two, two, and one/two, respectively. Each topic group contains 15 questions, and each question has a 7-point Likert scale, ranging from strongly disagree to strongly agree, where the respondent's beliefs, perceptions, and attitudes are measured. Although the types of questions are a closed form, the respondent can

TABLE 5
Survey of System Feature Satisfaction

The topic of system feature	Avg. score of satisfaction (1–7)	Avg. rate of open-ended answer (%)	Respondents
Instructional feedback (voice)	5.82	14.30%	Students
Instructional feedback (clicker)	4.19	7.06%	Students
Social feedback (head movement)	4.67	32.22%	Instructor
Instructional feedback (voice)	4.33	23.33%	Instructor
Instructional feedback (clicker)	4.33	17.78%	Instructor
Integration of proposed CFS with e-Learning system	5.33	13.33%	Instructor

provide extra comments (i.e., open-ended answers) for each question. For each topic group, three questions are designed to measure after-scenario satisfaction, eight questions to measure the topic's usability, and four questions to measure the features of this topic for learning/teaching impact.

After eight weeks of system evaluation, the results collected from three instructors and 204 students are summarized in Table 5. Because the social feedback channel is operated in the background, the students knew that the mechanism was working but did not feel it. Thus, only instructors attended the survey of the social feedback channel and the integration of a CFS with the e-Learning system. The average score of satisfaction reflects the system usability. The rate of open-ended answers may express the intensity of confusion, suggestion, interest, or suspicion of the question's content.

For the student respondents, the scores show that "instructional feedback (voice)" is preferable to "instructional feedback (clicker)", in contrast to instructor respondents. Instructional feedback (voice) has a higher rate of open-ended answers, as most of the opinions are about the complaint of the voice input problem. Some of the students' open-ended answers are meaningless such as unknown, not sure, none, and N/A. Based on the student respondents, we can observe the learning impact of our proposed system.

However, from a teaching perspective, the instructor respondents give a greater score to "social feedback (head movement)" than "instructional feedback (clicker/voice)", and with more open-ended answers. Obviously, the instructors have contributed many open-ended answers for this survey, although there are only three people. Most of the instructors' open-ended answers are just adding notes for their selection. We also found that many instructors are confused by the term "social signal" because they are not familiar with this subject. Before using the system, the instructor may need to think about how to utilize the social feedback channel for their teaching. In addition, some instructors praise the innovation of the social feedback channel as it helps them to observe the students. This is not what we wanted, as we expected the social feedback channel to take on the role of the social interaction of learning and teaching, which transmits implicit and non-verbal messages with some social functions such as interpreting atmosphere, real insight, silent agreement, or mental expectation.

The "instructional feedback (clicker/voice)" channel is to simulate the use of a clicker CFS. Lower scores show that this type of system may not be that interesting. Moreover, asking a question in class and hoping students will answer it by CFS is not a formative but a summative assessment, because the students are not in charge, and it therefore does not provide individual feedback to each student for trying again. By contrast, the "social feedback (head movement)" channel has some part of a formative-assessment function by collecting all the students' learning atmosphere at the same time, and then providing some feedback for students from the adjustment of the instructor's teaching practices. Because the social signal is implicit and informal, students are more likely to reveal their learning obstacles through unperceived body language such as head movement. Consequently, an instructor can recognize when students are struggling and immediately address the solution to the problem.

Finally, "the integration of the proposed system with an e-Learning system" receives a good score and draws fewer negative comments from the instructors. This shows that it is very important to provide integrated services for instructors in a complicated digital classroom environment.

7.3 Interactivity Analysis of Proposed CFS

Based on the satisfaction survey, we conducted further analysis on the interactivity of the proposed CFS. The approach used data transformation to convert the original data values into the data format suitable for interactivity evaluation. Data transformation can be divided into two steps:

1. The first step is the data semantic mapping process, which creates data element mappings from an original satisfaction viewpoint into an interactivity viewpoint. For this reason, 60 questions have been mapped to 10 items of instrument proposed by Keng et al. [25], which can measure the individual degree and overall degree of interactivity on a CFS. The mapping process produces a 60×10 mapping matrix. For each row of the matrix is a weighting vector for each question in terms of the corresponding 10 items of interactivity. The weighting vector is decided by senior instructors who inspect the relative proportions of each question on interactivity.
2. The second step is the code generation process, which creates an executable and scalable program that takes the data record interacting with the mapping matrix, in order to deal with the substantial dataset automatically.

After the data transformation processing, the satisfaction data set has been transformed into a new data set. Based on this new data set, we model the relationship between a scalar response variable Y (interactivity) and 10 predictor variables X_i (10 items of interactivity). Given coefficient estimates β_i, we can initiate the multiple linear regression formula:

$$\begin{aligned} Y_{Interactivity} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 \\ + \beta_6 X_6 + \beta_7 X_7 + \beta_8 X_8 + \beta_9 X_9 + \beta_{10} X_{10}, \end{aligned} \tag{2}$$

X_1: interact with the instructor/students
X_2: involved in learning/teaching
X_3: engaged in class
X_4: attentive in class

TABLE 6
Least Squares Coefficient Estimates

	Coefficient	Std. error	t-statistic	p-value
Intercept	1.2837	0.1632	7.866	<0.0001
X_1	0.0161	0.0051	3.157	0.0018
X_2	0.0136	0.0045	3.022	0.0028
X_3	0.0494	0.0026	19.176	<0.0001
X_4	0.0522	0.0057	9.158	<0.0001
X_5	−0.0021	0.0089	−0.236	0.8137
X_6	0.0376	0.0177	2.124	0.0349
X_7	0.0001	0.0016	0.063	0.9498
X_8	0.0085	0.0018	4.722	<0.0001
X_9	0.0162	0.0039	4.153	<0.0001
X_{10}	0.0043	0.0021	2.048	0.0418

X_5: participate in class discussion.
X_6: students provide opinions to instructor's questions
X_7: students receive feedback on their understanding of the course materials.
X_8: students receive feedback from the instructor
X_9: students realize the extent of following the course materials
X_{10}: students assess their understanding of the course materials with peers

To minimize the sum of squared residuals, the estimated least squares coefficient is calculated and presented on Table 6.

Table 6 displays the multiple regression coefficient estimates when the 10 items of interactivity (predictors) are used to predict interactivity (response). We can interpret these results as follows: for a given amount of $X_{j!=i}$, adding an additional unit on X_i leads to an approximate increase in interactivity by the coefficient value units. More concretely, for example, for a given amount of X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, and X_9, adding an additional unit on X_{10} leads to an increase in interactivity by approximately 0.0043 units. Because X_3, X_4, $X_{8,}$ and $X_{9,}$ have a higher coefficient value, we can interpret that the corresponding interactive item (X_3: engaged in class, X_4: attentive in class, X_8: students provide opinions to instructor's questions, X_9: students realize the extent of following the course materials) are the main features of interactivity on our proposed CFS system. The small p-values in X_3, X_4, $X_{8,}$ and $X_{9,}$ are also present in that there is an association between the predictor and the response. On the other hand, a lower coefficient value such as X_5 and X_7 with high p-values may reveal that our proposed CFS system may not be good on the facilitation of "X_5: Instructor/students participate in class discussion" and "X_7: Students receive feedback on their understanding of the course materials".

The limits of interactivity mentioned earlier in Section 3 are also worthy of discussion if we want to conduct effective CFS in the classroom. With respect to the dual-channel feedback mechanism, we discuss the possibility of lifting the limit of interactivity.

1. The elasticity of class time: this is fixed and constrained in a traditional classroom. Thus, maximizing the interaction between teaching and learning in the limited temporal period leads inevitably towards the increase of the bandwidth of interactive media. A dual-channel feedback mechanism can provide such an enhanced bandwidth for communication and then increases the possibility of improving learning/teaching effectiveness.
2. Students' participation: for each student to answer the instructor's question is regulated one at a time, but with a dual-channel feedback mechanism, this could be changed. The social feedback channel could collect all the students' nonverbal responses at the same time and accordingly broaden their participation.
3. Students' motivation: students may lack motivation to express their opinions in class. With the dual-channel feedback mechanism, students are more likely to reveal their learning difficulty through unperceived body language such as head movement. Consequently, the learning atmosphere has been reformed, and students' motivation can be promoted. During the experiment, we observed that students engaged with the instructional feedback activity more aggressively when they knew the system was watching their nonverbal head movement.
4. The lack of teaching-learning synchronization mechanisms: the main use case of the social feedback channel is providing the necessary support to the primary teaching activities or practice. Specifically, the social feedback channel can be viewed as an ancillary channel for the cooperation of the instructional feedback channel. When an instructor uses the instructional feedback channel to conduct a teaching activity, the social feedback channel plays an ancillary role to reflect the implicit learning atmosphere that was produced from executing the instructional feedback channel activity. Hence, reflecting the implicit learning atmosphere by the social feedback channel was a synchronizing tool for an instructor to coordinate learning with teaching.

8 Conclusion

The educational environment has been incrementally changed by effectively introducing new technology. With the aid of the innovative CFS technology, instructors can use technology to enhance their students' learning as well as their own teaching methods and practices. However, Kalantzis et al. [29] stated that, even when technologies for teaching and learning are well-conducted, the impact sometimes seems insignificant and the results seem disappointing. If learning in the classroom is replaced by online e-Learning, do the social relations of knowledge and learning necessarily change for the better or at all? If some of the teaching practices are executed by a machine or robots, does it change the nature of our teaching system? Technology, in other words, need not necessarily bring a significant change but a practical benefit.

We have presented a beneficial dual-channel mechanism for a classroom feedback system in a digital classroom environment, which contains two types of agent programs, namely learning and teaching agents. The learning agent provides instructional and social feedback to the teaching agent. The social signals collected by the learning agent are inferred from the head movement of the students, whereas the instructional signals are the spoken keywords recognized by a speech recognition engine. Using the head movement as a kind of social feedback mechanism is a unique feature for the proposed system. The learning agent is installed on a computer in front of the student. The teaching agent, installed on the instructor-side computer, is an e-Learning system equipped with a teaching dashboard to collect, summarize, and display feedback signals from the learning agents.

However, how to make the two feedback channels synchronously work together to enhance the pedagogical interactivity between the teachers and students is still untapped. It will be an interestingly extensive research area. In the future, we will develop algorithms to recognize more complicated patterns of head movement to identify lethargic or sleeping students. Such information could be included in the dashboard to provide a more nonverbal observation for the instructor. Also, with the popularity of using smartphones, it is a natural trend for the future CFS to use smartphones to replace the clicker or other learner-side devices. Finally, a CFS, integrated with courseware or e-Learning software, is very likely to be deployed in a classroom. A well-designed CFS helps instructors to deliver learning activities effortlessly in a style of orchestration and choreography, and benefits both students and the instructor during the teaching and learning process. In other words, the proposed system is a meaningful basic step towards the aforementioned direction.

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