Integrating Sensors and Exploiting Sensor Data with GIFT for Improved Learning Analytics

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INTRODUCTION

The Generalized Intelligent Framework for Tutoring (GIFT) was constructed in order to make it easier to create intelligent tutoring systems (ITSs), develop a shared set of authoring tools to do so, and to enable research in ITS (e.g., Sottilare, Goldberg, Brawner, & Holden, 2012). ITS research takes many forms; as an example, some of this research is intended to support existing training simulations (e.g., Brawner, Holden, Goldberg, & Sottilare, 2011). Further, some of this research is in the manners in which to model a learner (Brawner & Goldberg, 2012; Goldberg, Sottilare, Brawner, & Holden, 2011). Some of these models of the learner are not solely based on interactions that they have within the environment, but also upon sensors (e.g., Brawner, 2017; Brawner, Sottilare, & Gonzalez, 2012). Such sensors can either be based in software, analyzing information such as system interactions and clicks, or hardware (e.g., DeFalco et al., 2017), with sensors which sense physical items such as posture or gaze.

With computer-based or simulation-based training, sensors are somewhat optional; the learner can interact with the system, take actions, make progress, learn, and perform other activities without the explicit need for monitoring. Certain domains, such as psychomotor training or medical skill training, however, require the use of a sensor to monitor and identify the learner's performance. Particularly, using sensors can benefit to assessment of the learner (e.g., Goldberg, Amburn, Ragusa, & Chen, 2017), providing a source of information to the rest of the system so that the learner with adaptive instructions and feedback.

Integrating and synchronizing data from heterogeneous sources of sensors can be somewhat complicated and challenging, especially in a psychomotor domain, since sensors can have their own sampling behaviors and data stream formats. For example, the experimenter utilizing sensor data would need to connect with the various data streams of various sensors during the data collection from an experiment with human participants. Synchronizing the different sources into a time series and analyzing them would be complicated. It is, thus, necessary to investigate a general and reliable approach to better exploit the sensor data as a series of data points indexed in a time order by synchronizing all the heterogeneous sources of sensors.

The goal of this paper is to provide what is the general approach to exploit heterogeneous sources of sensor data in various domains including cognitive and psychomotor domains. We choose to use and explore the GIFT capability since it provides a generalized framework for a computer guided adaptive instruction, and there are many pre-existing efforts which integrate sensors with GIFT. These sensor streams were able to provide rich learning analytics (Brawner, 2017; Brawner & Gonzalez, 2016; DeFalco et al., 2017). We examine the current capability and provide directions to extend the capability in order to better assess the learner performance in the diverse domain.. We also examine the process to integrate new sensors with GIFT, and provide suggestions for improved systematic process of integration.

To pursue the aforementioned goal, in this paper, we first review and summarize the current process of integrating sensors with GIFT, and identify the technical needs to synchronize multiple sensors for improved learning analytics. In addition, we report a use case from our exploratory study. We have created a study environment in GIFT, where a psychomotor skill can be assessed by sensors by extending an adaptive training on rifle marksmanship (Goldberg, Amburn, Ragusa, & Chen, 2017). A golf putting was selected as a psychomotor training task because it is physical and precision-required performance like rile marksmanship. It is argued that breathing techniques would affect the precision-required performance of rile marksmanship (e.g., Grossman & Christensen, 2008), and it is also suggested that a slow breathing skill can help individuals to improve accuracy on their performance in other tasks (e.g., Goldberg, Amburn, Ragusa, & Chen, 2017; Kim, Dancy, Goldberg, & Sottilare, 2017).

SENSORS INTEGRATED WITH GIFT

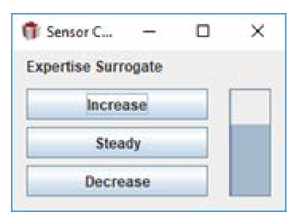
Several commercial and custom-built sensors have been integrated with GIFT to support learner assessments that include learner engagement, arousal, motivation, knowledge, anxiety, and engaged concentration. These learner states are defined in Table 1. It is reasonable to think that they can influence learning, as prior research has shown effects.

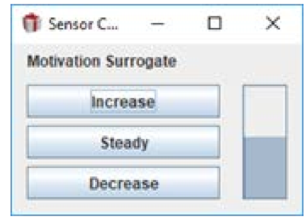
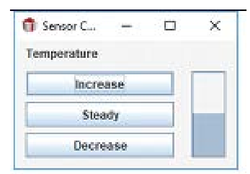
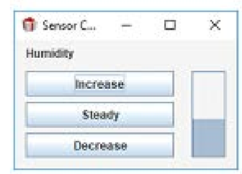
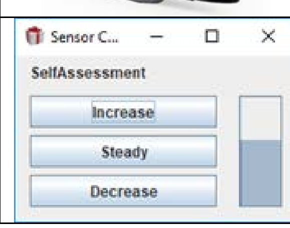
Table 1. Learner states tracked in GIFT.

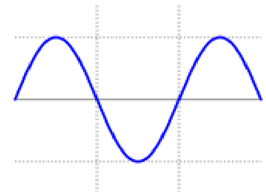
Learner States	Definition	References
Engagement	"refers to the degree of attention, curiosity, interest, optimism, and passion that students show when they are **learning** or being taught, which extends to the level of motivation they have to learn and progress in their **education"**	(The Glossary of Education Reform, 2016)
Arousal	"a major aspect of many learning theories and is closely related to other concepts such as anxiety, attention, agitation, stress, and motivation. One finding with respect to **arousal** is the Yerkes-Dodson law which predicts an inverted U-shaped function between **arousal and performance**"	(Clark, n.d.)
Motivation	"an internal **drive** that activates **behavior** and gives it **direction**"	(Rakus, 2011)
Knowledge	"a familiarity, awareness, or understanding of someone or something, such **as facts, information, descriptions, or skills**, which is acquired through experience or education by perceiving, discovering, or learning"	(Knowledge is a familiarity, n.d.)
Anxiety	"a feeling of **worry, nervousness, or unease**, typically about an imminent event or something with an **uncertain outcome**" (Anxiety [Def. 1], n.d.) "anxiety impacts a student's **working memory**, making it **difficult to learn and retain information**" (Minahan, 2012)	(Minahan, 2012)
Engaged concentration	"a state of engagement with a task such that concentration is **intense, attention is focused, and involvement is complete**"	(Baker, D'Mello, Rodrigo, & Graesser, 2010)

To support the assessment of the learner states listed in Table 1, we have developed interfaces for a series of commercial and customized sensors for use during GIFT instruction and developmental testing. A table of sensors integrated in GIFT are listed in Table 2, along with their descriptions, inputs, derived measures and a picture of the sensor hardware or surrogate.

Table 2. Sensors integrated with GIFT.

Sensor	Description & Inputs	Derived Measures	Picture
Zephyr Bio-harness	ECG, respiration, estimated core body temperature, accelerometer, time, and location	Heart rate (HR), breathing rate, heart rate variability, HR confidence, estimated core body temperature, impact, activity, caloric burn, posture, % HR max, % HR at anaerobic threshold (AT), accelerometer, training loads and intensities, jump, bounds, leaps, explosiveness, peak force, peak acceleration, GPS	
Emotive Emo-Composer (Alshbatat, Vial, Premaratne, & Tran, 2014)	As part of the Emotiv Software Development Kit (SDK), the EmoComposer is a testing tool for developers building EPOC headset applications	The derived measures are unique to each application developed	
Emotiv Epoc EEG Headset (Lang, 2012)	Brain control interface with 14 channels of EEG data	Instantaneous excitement, long term excitement, engagement/ boredom, frustration, and meditation	
ARL Expertise Surrogate	Allows tester to vary expertise or domain competency This surrogate is used for testing in place of any other measure of expertise (e.g., assessment/test).	Expertise or domain competency	
Microsoft Kinect	Allows users to act as the controller and interact with simulation elements using a combination of body movement and spoken commands IR Depth Sensor measures the distance of each pixel of an object from camera plane	Emotional states (facial markers); engagement (posture); arousal (acceleration measures)	

Microsoft Band 2	Optical heart rate sensor; accelerometer/gyro;; GPS; ambient light sensor; skin temperature sensor; UV sensor; capacitive sensor; galvanic skin response; microphone, barometer	Heart rate, steps, location, galvanic skin response (GSR) Resistance and GSR conductance	
ARL Motivation Surrogate Sensor	Allows tester to vary the motivation level of a user This surrogate is used for testing in place of any other measure of motivation (e.g., survey instrument).	Motivation level	
ARL Mouse Temperature & Humidity Sensor	Temperature and humidity of a user's hand	Arousal, stress	
ARL Mouse Temperature & Humidity Surrogate Sensor	Allows tester to vary temperature and humidity of a user's hand This surrogate is used for testing in place of the actual mouse temperature and humidity sensor	Arousal, stress	
Inertial Labs 3D Orientation Sensor (OS3D)	Changes to velocity (acceleration) and disturbances to magnetic fields	Real-time heading, pitch and roll orientation information	
Affectiva Q Sensor	Electro-dermal Activity (EDA), Temperature, Acceleration (3D)	Arousal, stress	
ARL Self Assessment Sensor	Allows tester to vary a user's self-assessment This surrogate is used for testing in place of any other self-assessment methods	Self-assessment of performance	

ARL Sine Wave Sensor	Allows tester to vary any user's attributes as sine waves This surrogate is used for testing in place of any other methods to vary learner attributes sinusoidally	Sinusoidal representation of learner attributes (e.g., engagement)	
USC Virtual Human Toolkit Multisense (Scherer et al., 2012)	A perception framework that enables multiple sensing and understanding modules to interoperate simultaneously, broadcasting data through the Perception Markup Language; includes the Generalized Adaptive View-based Appearance Model (GAVAM), Constrained Local Model (CLM) and Flexible Action and Articulated Skeleton Toolkit (FAAST)	GAVAM – head tracking CLM – face tracking FAAST - middleware to facilitate integration of full-body control with games and VR applications	

LESSONS LEARNED FROM INTEGRATING SENSORS WITH GIFT

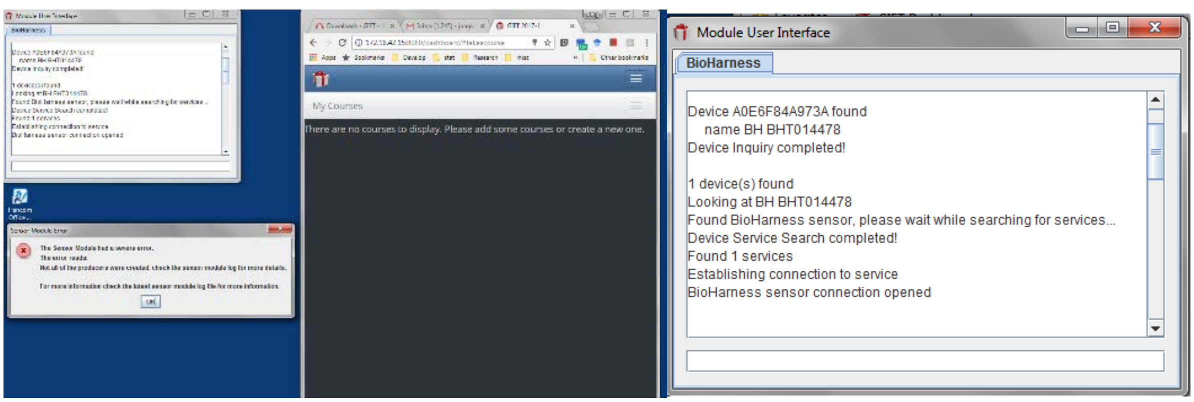
Besides the various sensors integration with GIFT shown in Table 2, it was identified that there is a challenge to expand the instructional domains. One goal for the design of GIFT is to expand the number and type of instructional domains in which it can support tutoring of both individual learners and teams (e.g., Brawner, Sinatra, & Gilbert, 2018; Sottilare et al., 2017), and tutoring of psychomotor tasks beyond the desktop environment (e.g., Sottilare, Hackett, Pike, & LaViola, 2017). We have been extensively involved in developing strategies (Sottilare & LaViola, 2015) and concepts for psychomotor tasks like marksmanship (Goldberg, Amburn, Brawner, & Westphal, 2014), land navigation (LaViola Jr. et al., 2015), and hemorrhage control (Sottilare, Hackett, Pike, & LaViola, 2017). Designing tutoring for the psychomotor domain has also influenced the selection and use of sensors to support assessment during instruction. For example, the land navigation task has necessitated the use of mobile devices (e.g., smartphones) and associated sensors to support assessment. We have also examined pressure sensors and designed how they might be used to assess the use of pressure bandages and tourniquets during combat casualty care to determine blood flow from wounds. As we more fully develop these concepts, we will also develop interfaces for the associated sensors and make them available in the GIFT baseline. In this section, we report the lessons learned from the use of sensors and sensor data analytics in a psychomotor task training.

An Example for Using a Smartphone Sensor with GIFT

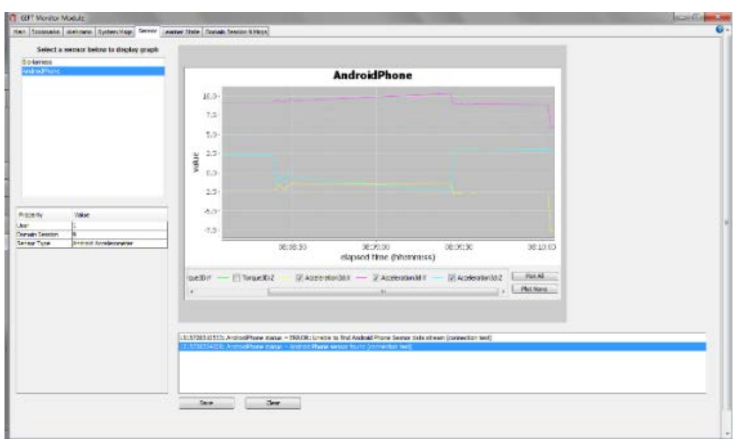
Integrating sensors with a system can be somewhat straightforward; it is suggested for the developer to simply follow the template for code, processing, and configuration. Any of the processing which has been authored for any of the sensors may be able to be reused for any of the other sensors with authored configurations. The "sine wave sensor" can be used to test out any individual item (connection, configuration, processing, etc.). Step 1 is to "make a sensor connection using one of the numerous interfaces", Step 2 is to "configure it with the configuration tool, probably just copy whichever sensor you used previously". For example, integrating the Android phone's accelerometer and gyroscope sensor into GIFT consists of a few basic steps. We, first, developed an Android app that can access the phone's sensor data and that can relay the data stream to the GIFT desktop. The streamed sensor data from the app are formatted as JSON, with timestamped UDP (User Datagram Protocol) packets to an IP address that is configurable from the app. Once the Android application was operational, GIFT could be modified to handle the incoming UDP packets. GIFT defines an abstract class which generically represents communication with a sensor.

An additional implementation of this class (`AbstractSensor`) was created to receive data from the Android phone's sensors. The class is named `AndroidPhoneSensor` and overrides `AbstractSensor`'s methods: `start`, `stop`, and `test`. The internal implementation of `AndroidPhoneSensor` starts a new thread when the `start` method is called. This thread continuously listens for the UDP packets from the Android device. When a packet is received, it parses it and places each of the six data measurements from the packet (three dimensions of accelerometer data and three dimensions of gyroscope data) into a `SensorData` Java object which is then sent to the Sensor Module's existing pipeline for processing by GIFT. Once the `SensorData` object has been sent to GIFT, the thread listens for another packet.

For implementations in the future, it may be beneficial to create an abstract implementation of `AbstractSensor` which receives JSON data via UDP and defers interpreting the JSON to drivers of the class. This would make the majority of the code written within `AndroidPhoneSensor` to be reusable and help separate common boilerplate code from the code which is specialized to a specific sensor.



(a) Initiating the BioHarness sensor through the Bluetooth connection.



(b) Visualizing accelerometer sensor data in GIFT, and the three axes in a smartphone accelerometer sensor.

Fig 1. The GIFT study environment for a psychomotor task.

Sensor Data Exploitation

After the sensor integration with GIFT, it is important to consider how to extract the features of the learner performance and behavior from sensor data obtained from sensors. Extracting and processing such data is called analytics. Particularly, when one considers the context of education and learning with a large amount of data, it is called learning analytics (LA) and educational data mining (EDM) (Baker & Siemens, 2014).

Previously, to assess the cognitive and affective states of the learner, researchers have tried to incorporate appropriate sensors into an ITS (e.g., D'Mello et al., 2005). In this line of research, the traditional method to exploit such sensor data for intelligent tutoring is largely dependent on the offline post-processing of the data rather than a real-time model of data analytics (Brawner, 2017) – i.e., taking measurements in a classroom, storing and moving to the offline environment, performing data analytics, and generating a model for the next set of classroom learners. The traditional method is not real-time, which seems to be hard to address varying learning environments. It would be, thus, necessary to advance learning analytics (i.e., an improved real-time assessment model), but it would create another set of problems in the ITS operation since the sensor data could be infinite, outside of control, and strictly constrained by time (Brawner, 2017).

Similar to the affective data exploitation (Brawner, 2017), and the learner logging data processing from a tutor interaction (Baker & Siemens, 2014), sensor data in psychomotor tasks may require us to develop a methodology for efficient data processing and analysis for knowledge discovery, and to compare the sensor data with a theory-based model. A psychomotor task is usually characterized by coordinating cognitive, physical, and physiological variables in executing actions. Thus, sensors are focused on measuring the coordination of the learner features, which can be used to understand the learner according to the features. The physiological data, such as the heart and respiratory rate can be measured using a bioharness strap (e.g., Goldberg, Amburn, Ragusa, & Chen, 2017). Also, acceleration data can be collected and analyzed to identify motions and movements (e.g., Fehlmann et al., 2017; Shamoun-Baranes et al., 2012).

As shown in Fig. 1, we have created a study environment in GIFT where two heterogeneous sensors are combined to measure the learner features. In a pilot testing of the study environment, a participant is to be instructed to learn the breath control skill through a GIFT course, and then to perform a series of golf putting tasks: (a) 5 putting trials under a regular breathing, and (b) 5 putting trials under a tactical breathing condition. Fig. 2 shows plots of the collected sensor data with the time frame from 2:30 to 5:30, which is under a regular breathing with 5 putting trials.

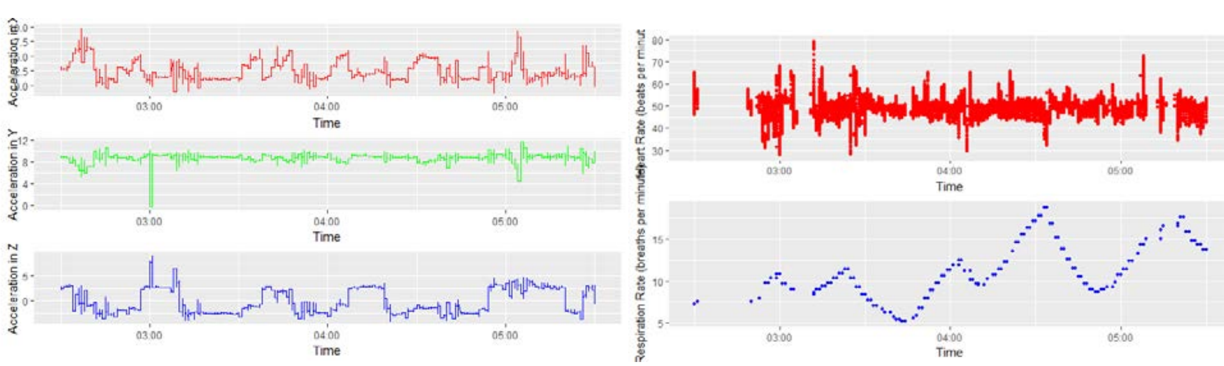


Fig 2. An example of the sensor data.

The Learner Assessment

The current GIFT capability does not fully support the combined sensor data analytics in real time. We report that we have conducted an offline sensor data analytics. We approach learning analytics of the two heterogeneous sensor data from the bioharness strap (e.g., respiratory rate as breath per minute) and the Android phone accelerometer (e.g., the tri-axial values).

We have explored the extended cognitive modeling approach that is based on the ACT-R architecture (Anderson, 2007), and extended to account for a physiological system, called ACT-R/Φ (Dancy, Ritter, & Gunzelmann, 2015). A version of the physio-cognitive model has been implemented (Dancy & Kim, accepted; Kim, Dancy, & Sottilare, submitted), and explored to predict physiological variables (heart and respiratory rates).

Previously, a cognitive model has been used to track knowledge of the learner and to conduct performance assessment in an ITS (Anderson, Boyle, Corbett, & Lewis, 1990; Corbett & Anderson, 1995). This work, however, has been limited to the cognitive task domain in a desktop learning environment. We start to utilize the physio-cognitive model to track the learner knowledge and to predict the learner performance in an attempt to achieve a (near) real-time sensor data analytics in a psychomotor task training.

The leaner models, that can be cognitive (e.g., Anderson, Boyle, Corbett, & Lewis, 1990) or (and) physiological (Dancy & Kim, accepted) based models, can be used for assessing the learner as well. Based on the assessment process, we can provide more reasonable adaptive strategies for training. For example, in a tactical breathing practice, the learner would practice with a 4-4-4-4 cycle of breathing (4 s for breathe-in, 4 s for hold, 4 s for breathe-out, and 4 s for hold). However, the lung capacity or the tidal volume would be different by individuals (e.g., by gender, by age, etc.). A precise and correct learner model can be essential to determine whether a training regimen would be cognitively and physiologically plausible. These aspects of learning can be analyzed through the sensor data exploitation to support improved learning.

Along with the physiological responses, we also explored the sensor data of acceleration. The raw acceleration data is tri-axial, and shows variable changes in values in terms of the xyz axes. The raw data can be processed to recognize movements and motions. That is, acceleration data can be static that is dependent on gravity, and it can be also converted to the dynamic feature of performance as well—e.g., the vectorial dynamic body acceleration can be computed using the dynamic components of the signal to assess the activity level of the individual with three axes all together ($\sqrt{x^2 + y^2 + z^2}$) (Fehlmann et al., 2017).

To further exploit the sensor data of acceleration, it may be helpful to transform the complex signals to another domain. The key idea is to decompose a complex signal in the time domain to the frequency domain through Fourier transform. To identify oscillations in the dynamic body acceleration for each axis, it has been reported that it is possible to compute power spectrum densities (PSDs) and their associated frequencies using Fourier analysis so that we can figure out at which frequency the signal varies the most, indicating a large movement (Fehlmann et al., 2017). Based on this approach, behavior of animals has been investigated to identify six broad states of motions and movements including walking, standing, running, resting (sitting or lying), grooming, and foraging. This technique can be useful to conduct data processing of heterogeneous sensor data collected in a time series manner (e.g., GPS and acceleration sensor data). With regard to the aforementioned psychomotor related sensor data, a machine learning technique (e.g., random forest) can be used to classify a psychomotor task with the leaner data such as sitting, walking, backswing, hitting the golf ball, etc. The sensor data is also worth exploring to predict the learner behavior by validating the model. Brawner (2017) explored machine learning algorithms to address the real-time analytics with cognitive-affective sensor data, highlighting the best real-time model with the learner features is based on offline experimental data validation with a machine learning technique.

DISCUSSION AND CONCLUSIONS

We briefed the use of sensors with GIFT, specifically in the psychomotor task domain. In general, integrating sensors can be relatively considered as a simple process, but interpreting sensor data from multiple sources in a time series manner would be complex and challenging.

Sensor Data in the Psychomotor Domain

In our study environment, the learner's behavior and performance (i.e., golf putting trials with the breath control skill) can be decomposed to physical, physiological, and cognitive components. On the onset of the tactical breathing course in GIFT, the sensor data collected from a smartphone is sampled and is relayed to the GIFT desktop. The acceleration data shown in Fig. 2 is complex. shows changes in values within a specific time window and by a series of certain physical motions and movements. A further analysis based on a machine learning technique is needed to reliably cluster and classify changes in the tri-axial values of acceleration, and to identify postures and movemnets, and to implement a model (e.g., a backstroke, hit, follow-through).

We recorded the participant's activities (i.e., when the participant starts to perform a slow breathing and a putting trial) by using the Bookmark functionality in GIFT. The Bookmark function affords a record-keeping by an experimenter (or a data collector)—i.e., the timestamped annotations in terms of the participant's actions. The annotated data can be later matched to the sensor data, and then the data can be labeled by postures and movements.

As an offline analysis of sensor data, we tested a couple of R packages. We found it useful for data analytics and the learner performance assessment. Now the question is how to adopt the approved operational procedures of offline anlaysis, which attempts to strenghen the GIFT capability. With the pilot testing data, we computed the acceleration raw data to obtain different aspects of the data (e.g., static and dynamic acceleration, vectorial dynamic body acceleration, power spectrum density of acceleration signals). The acceleration data can be mainly categorized into two aspects—static and dynamic. The static acceleration is dependent on gravity, describing postures, and the dynamic acceleration describes dynamic body movements (Fehlmann et al., 2017). Besides the acceleration data from a smartphone, the GPS data can be also explored to investigate movements and motions—e.g., Behavioral Change Point Analysis (Gurarie, Andrews, & Laidre, 2009).

The sensor data regarding the physiological component can be interpreted to identify the breath control skill during the physical performance. In the pilot testing, we collected data from the Bioharness that tranmits data through Bluetooth. The participant did wear the Bioharness with the chest strap during the peroformance. It is observed that the respiration rate (breath per min) looks increasing within the specified time window. We delved into what theory can describe our sensor data. We chose to use a computational model in a cognitive architecture becasue it can support learning and skill development processess of humans (e.g., Anderson, 2007). Particularly, we implement a physio-cognitive model (Dancy & Kim, accepted; Kim, Dancy, & Sottilare, submitted), which can be used to account for cognitive learning theories (Kim, Ritter, & Koubek, 2013) with physiological features of the learner. The physio-cognitive model supports plausibility of human learning behavior since it is based on a cognitive architecture, ACT-R (Anderson, 2007). That is, the physio-cognitive computational model can support creating a tailored training scenario that can meet cognitive and physiological constraints of humans (e.g., the varying tidal volume of men and women).

The sensor data is usually of a form of osciliations in a time series manner. For effciency of calcuation, the sensor data in the time domain) can be transformed to the frequency domain through Fourier transformation, spectral analysis. This approach has a potential to extend and improve our understanding of the learner behavior (e.g., Fehlmann et al., 2017; Xu & Reitter, 2017). Supposed that an intelligent tutoring system with multiple sensors and with multiple individuals as a team. The aforementioned method, an understanding of power spectrum density of the signals, can be applied to a team performance analytics, e.g., team communication and team collaboration through a dialogue. There is a study about dialogue behavior and effectiveness of conversations, arguing that the spectral analysis can be successful to measure communicative effectiveness (e.g., a successful task collaboration) by considering the alignment of certain linguistic markers, lexical items, or syntactic rules between interlocutors correlates with task success (Xu & Reitter, 2017).

Sensors and Standardization

Recently, we have been involved in developing proposals for standardizing data messaging and interactions between components of adaptive instructional systems (AISs) as part of an IEEE standardization study group. Both sensors for data acquisition and algorithms for state classification may be influenced by the defined functions and information shared between AIS common components. As the types of tasks supported by GIFT expand and as standards take hold in the AIS community, we envision GIFT and its sensor options being updated to optimize models of the learner as a basis for adaptive instruction, which can provide the starting point for standardization (Sottilare & Brawner, in press).

Multiple Sensors and Multiple Learners as a Team

A major design change challenge will also influence the type of sensors and their use in GIFT. With the expansion in GIFT capabilities from individual learner tasks to team tasks, we predict a need for a multi-sensor architecture to track the behaviors of multiple team members in support of team taskwork assessments. Sensors will be needed to disambiguate individual learner data (e.g., position, location, communication) from others on the team to provide individual, subgroup, and group feedback. This is required to provide a model of how individual actions roll up to the attainment of team goals.

Methods of assessment will become more complex as we move from desktop applications to live, augmented, and mixed reality applications. Complexity will also rise as we move from individual to team instructional constructs. The groundwork laid to support individual task domains will largely be reused to support team instruction, but additional team models will be required and team assessments will require logic to understand how individual behaviors and roles influence progress toward team goals. Sensors will continue to play a part in team assessments, but can be provided and extended in the same manner that individual models are extended to team models (Brawner, Sinatra, & Gilbert, 2018).

We are planning spiral development for team model development for adaptive instruction. Initially, we will construct team models that focus only on team measures to simplify the assessment problem. Sensors will be needed to assess whether team objectives have been met. We believe this initial approach will be accomplished with little change to the GIFT architecture as it is today, but more hierarchical modeling of teams in the future spiral phases of development will require methods to link individual learner models and individual roles and responsibilities to team models and objectives. This will require some fundamental additions to the current GIFT architecture. Sensors will be required to disambiguate data from individual learners who may be operating in close proximity in live training environments. Standardizing approaches for different types of team tasks may lead us to more simplified approaches to sensor integration for team tasks.

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