Estimating Children's Characteristics by Observing their Classroom Activities

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***Abstract*— Good teachers recognize how each of their students is different from the others and adapt how they support them. We replicate such a capability to understand the individual specificities of children. Our approach observed the social signals of fifth graders based on their daily classroom behavior using a sensor network. We used depth cameras to track their positions and identified them with RGB cameras. We observed 84 children (three classes) and used these results to estimate school-related children's characteristics: self-efficacy, performance-goal, and exam scores. The estimation yielded 73.0-74.7% accuracy for the target variables.**

I. Introduction

Previous studies explored the potential use of social robots in classrooms. For instance, they were used for language education in a classroom [1, 2]. Social supportive behavior improves the teaching of foreign languages [3]. Howley et al. found that it was easier for students to get help from a robot teacher than a human teacher [4]. These studies show a promising direction to use social robots for supporting children's learning.

Previous research also unveiled the possibility to use social robots to support children's social life. For instance, Woods et al. explored how differently children talk to robots about their bullying and/or victimization experiences [5]. Bethel et al. concluded that since children's memory as an eyewitness is less influenced by a robot interviewer than a human, a robot could be used to investigate sensitive events [6]. Previous studies indicated that a robot can be a close partner for children. Tanaka et al. revealed that a robot successfully interacted with children for five months and was accepted as a peer [7].

However, a relatively underexplored topic is how to 'understand' an individual child in a school or other group settings. For instance, teachers comprehend the academic skill and the personality of their students [8]. Such 'understanding' would be useful for social robots, too. One pioneering finding was reported by Leyzberg et al. who argued that tutoring performance is improved when a robot adapts its teaching strategy to individuals [9]. Nevertheless, little is known about how a robot grasps children's school-related personal traits.

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Fig. 1 Differences of children's school-related personal traits

This study's goal is to develop a technique to estimate the individual differences of children by observing their social signals in a classroom to ameliorate future social robots in schools (Fig. 1).

II. Related Work

A. *Techniques for Observing Individuals' Behaviors in Group Settings*

Advances in robotics and ubiquitous computing have greatly improved observation techniques for individual behaviors. Even though such devices as RFID tags and smartphones can track the behaviors of the people carrying them, demanding that children always have them is problematic and unrealistic. Without asking them to carry a device, we can still identify individuals from their faces [10]. Nonetheless, one limitation of face-based identification is that it can only identify people whose frontal face is observed by a camera. Thus, only with it, people's behaviors are not well perceived. Instead, researchers have explored various techniques to combine tracking technique with person identification (e.g., [11-13]).

Our study includes an approach that integrates person identification with tracking. Unlike previous studies, we use depth camera for tracking, which yielded better tracking performance than tracking methods with RGB cameras [14]. We expect that our system will provide more robust results when tracking children's behavior in a crowded classroom.

B. *Estimating Characteristics in Group Setting*

Various techniques have been developed for understanding individuals from their behavior, typically with wearable devices. For instance, Choudhury et al. developed a wearable device called a sociometer that records contact between device carriers, which provide useful information for analyzing people's face-to-face interaction on social networks [15]. Similarly, children's friendships were estimated with proximity information observed with RFID tags [16]. Olguín et al. developed a technique to recognize such daily activities as talking with others and being at particular locations using a wearable sensor and found that such personality traits as extraversion and openness correlate with the perceived activities [17]. Kalimeri et al. applied support vector machine (SVM) classification to data obtained from wearable sensors and classified personality with 50-70% accuracy (better than a chance ratio of 33%) [18]. Mohammadi et al. analyzed the prosody of people's speech and developed 2-class classifiers for personality with 60-72% accuracy (better than a chance ratio of 50%) [19]. These studies revealed the possibility of estimating individual's personal traits from behavior data, although techniques still need enhancement, especially for better accuracy and other personal traits beyond personality.

In contrast to these previous studies, our study introduces information acquisition from a sensor network without wearable devices on a population of children in a classroom context for identifying personal traits: self-efficacy.

C. *Children's Personal Traits in Classroom*

Numerous studies on school-related personal traits have concentrated on pupils in psychology and education research. Among them, we focused on self-efficacy and performance-goal, each of which represents critical aspects of children's activity in the classroom: learning and social life.

Self-efficacy: self-efficacy is defined as the "[belief] in one's capabilities to organize and execute the courses of action required to manage prospective situations" [20]. In a classroom, it represents whether a student believes she can manage her own learning. Children with high self-efficacy tend to learn and have more success, generally in a self-regulatory manner. For instance, children with high self-efficacy tend to seek help when needed, but children with low self-efficacy tend to avoid that step [21].

We believe that awareness of the self-efficacy of each child is beneficial for a social robot in a classroom. If it could identify each child's self-efficacy, it would be able to adjust its proactivity when offering help, e.g., offering more proactive assistance to children suffering from low self-efficacy.

Performance goal: performance goal is the motivation of a student for learning, but it is quite different from self-efficacy. It refers to whether the student's learning goal is to get better scores than the other students and more attention from teachers [22]. For students with a high performance goal, competing with other students is the primary concern. Students with high performance goals tend to study hard and achieve better exam performance [23].

We consider that knowing performance goals in addition to self-efficacy will be beneficial. We assume that if a robot could recognize them the robot could change its learning support behavior to stimulate competition for children with high performance goals.

III. System Design

Figure 2 illustrates the architecture of our developed system, which was originally developed [24] to estimate social status for children; in this study we used it to estimate different characteristics. Our *observation system* estimates children's positions by integrating both a people tracking system and a face identification system. When the faces of the children are identified, their IDs are associated to the tracked entity in the tracking system. The *estimation system* predicts the children's personal traits based on the extracted features from their positions by the *observation system*.

A. *People Tracking*

We employed a previously proposed people tracking algorithm using depth sensors [14], where depth cameras were attached to the ceiling and their positions and heights were estimated based on head- and shoulder-shape detection. With our setting, the tracking system monitors the position of all the people in the area at 30 Hz with an accuracy of approx. 30 cm. This system has robustness toward illumination changes and clothing colors because it uses depth information, which is useful for a classroom that has sunshine from windows. Since the depth-camera views from the top down, it is robust for crowded situations.

We arranged the locations of the depth sensors to efficiently cover the space. The sensor (Kinect, field of view (FOV) is 57° horizontally and 43° vertically) covers approx. a 4 m * 3 m space when attached to the ceiling at 2750 mm. With 24 depth sensors, 8 by 16 m of the room was covered. Fig. 3 shows a depth image from a sensor and the tracking result in the classroom, where four to five children are sitting around their desks. The system tracked them well in such crowded situations.

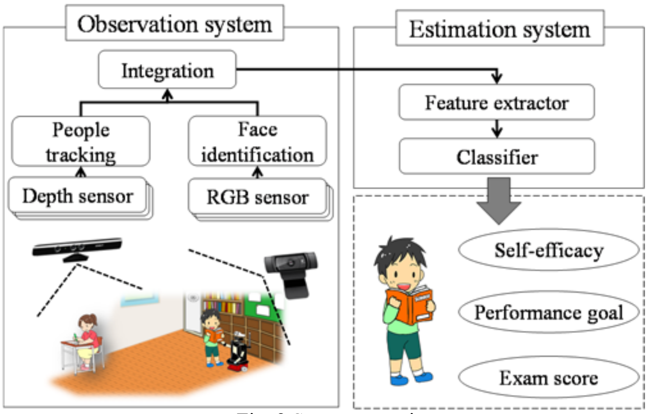

Fig. 2 System overview

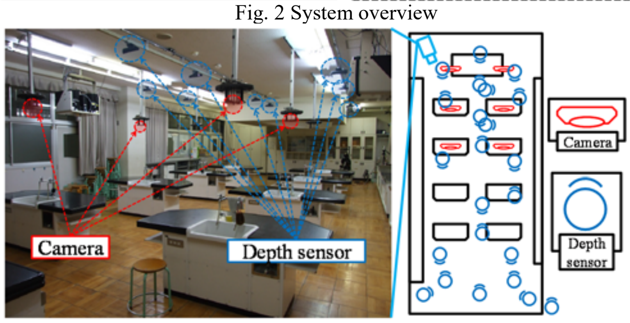

Fig. 3 Sensor arrangement

B. Person Identification

For person identification, we employed a face identification approach using RGB cameras and a commercial face recognition software package (Omron, OKAO Vision [10]).

We designed the camera configurations for adequate balance between the number of cameras and the chance of face identification. Since OKAO Vision requires that faces be observed in the frontal direction within 20 degrees (pitch) and 35 degrees (yaw), we need many cameras to increase the chance of observing the frontal faces. However, the school insisted that cameras not obstruct class activities. For instance, the cameras should not distract the children during class (e.g., no cameras on desks facing the students) or obstruct them from seeing the teacher or the blackboard. They should also be put higher than an adult's height to avoid collisions. Here we assume that children will at some point look toward the front of the classroom, where the teacher usually stands, and so for each desk, we put only one camera that should capture all of the children at or near that desk. That is, we set six RGB cameras (Logicool, C920t, FOV is 70.5° horizontally and 43.6° vertically). The details of the performances of person identification were previously reported [24].

C. Features for Estimating Personal Traits

Time spent alone: We measured the ratio of the time that children spent alone. For each child i and each time t, we computed whether other children were within a threshold (D_{TH}) of this child. If someone is present in the threshold, the child is judged as not being alone at this time:

$$Time\ spent\ alone(i) = \frac{1}{ObsTime(i)} \sum_{t=t_0}^{t_n} (isAlone(i,t) \cdot \Delta t) \quad (1),$$

$$isAlone(\mathrm{i}, \mathrm{t}) = \begin{cases} 1 & if(dist(pos(i,t), pos(j,t)) > D_{TH}\ for\ all\ j (j \neq i)) \\ 0 & otherwise \end{cases} \quad (2),$$

where $ObsTime(i)$ is a function that returns the total tracking time of child i, Δt is the time step (33.3 msec) for this calculation, $pos(i,t)$ is the x-y position of child i, and $dist$ is the Euclidean distance between two x-y vectors. We used multiple thresholds for D_{TH} : 500 mm for the intimate distance and 1200 mm as the collaboratively working distance.

Moving distance: We measured the average moving distance of the children per second:

$$Moving\ dist(i) = \frac{1}{ObsTime(i)} \sum_{t=t_0}^{t_n} (\ dist(\ pos(i,t), pos(i, t+\Delta \mathrm{s})\ )\ ) \quad (3),$$

where we set Δs as 500 msec to decrease the effects of tracking noise.

Moving distance outside their own desk areas: In the class activities, children were split into groups and assigned to desks. While children often worked within the area of their desks, sometimes they moved around the classroom. We measured the average travel distance during these situations. Here a child is judged as being outside of his/her own desk area if the distance from the desk exceeds a range threshold (R_{TH}). The following is the computation for feature

$$MovingdistOutside(i) = \frac{1}{ObsTime(i)} \sum_{t=t_0}^{t_n} (isOutside(i,t) \cdot dist(pos(i,t), pos(i, t+\Delta s))) \quad (4),$$

$$isOutside(i,t) = \begin{cases} 1 & if(dist_m(pos(i,t), desk(i))) > R_{TH} \\ 0 & otherwise \end{cases} \quad (5),$$

where $desk(i)$ is the rectangle area of child i's assigned desk and $dist_m$ is the shortest Manhattan distance between the position and the rectangle area on the x-y plane (y is the classroom's long side). We set R_{TH} to 300 mm for situations where children change their own positions around the desk and 600 mm for situations where they go to other desks.

Sitting time: We measured the ratio of the time when children were sitting based on the observed height of their heads. If a child's head location is below height thresholds (H_{TH}), he/she is judged to be sitting:

$$Sitting\ time(i) = \frac{1}{ObsTime(i)} \sum_{t=t_0}^{t_n} (isSitting(i,t) \cdot \Delta \mathrm{t}) \quad (6),$$

$$isSitting(i,t) = \begin{cases} 1 & if(HeadHeight(i,t) < H_{TH}) \\ 0 & otherwise \end{cases} \quad (7),$$

where $HeadHeight(i,t)$ is the measured height of child i. We used two H_{TH}: 1050 mm for sitting and 1200 mm for half-sitting situations (like working at the desk).

Number of surrounding people: We measured the average number of surrounding people. For each child and each moment, we computed the number of other people within a distance threshold (D_{TH}) from him/her:

$$Number\ of\ surrounding\ people\ (i) = \frac{1}{ObsTime(i)} \sum_{t=t_0}^{t_n} \sum_{j=\forall j} (if(dist(pos(i,t), pos(j,t)) < D_{TH}). \quad (8)$$

Time spent around the robot: We measured the ratio of the time that the children spent around the robot. For each child and each moment, we computed whether the child was within a distance threshold (D_{TH}) from the robot:

$$Spent\ time\ around\ the\ robot(i) = \frac{1}{ObsTime(i)} \sum_{t=t_0}^{t_n} (if(dist(pos(i,t), pos(robot,t)) < D_{TH}) \cdot \Delta t)\ . \quad (9)$$

D. Classification System

In this study, in addition to the two personal traits (*self-efficacy* and *performance goal*), we estimated exam scores and classified them as *high* or *low*. The *low* class includes children whose scores are below average. We applied support vector machine (SVM) for classifications and used different combinations of the above features to construct each SVM classifier for all of the personal traits and exam scores. Below we explain which features we used.

IV. Data Collection

A. Participants

Our 84 participants were three classes of 5th graders (14 females and 14 males in each class) whose average height was 147.2 cm (S.D. was 9.4). The experimental protocol was approved by our IRB and school administrators. All the children and parents signed consent forms and agreed to be video-recorded.

B. Environment

We conducted data collection in an elementary school's science room about twice a week per class. Four to five children sat around each desk (six desks from the front are used) during 45-minute lessons that are followed by a five to twenty minute break.

C. Robot's Task

In this data collection, we installed a robot in the room to increase the children's understanding of their science lessons. The robot interacted with children by quiz-style conversations whose contents were prepared from lesson materials. With the quizzes, children can review their recent lessons. For this study, the robot was semi-autonomously controlled and was only available during breaks before/after classes. Further details about the robot are available [25, 26].

D. Procedure

Each class had four lectures during the study. The room remained open before and after the science lessons. Among the four lectures, breaks during the two lectures were with the robot. The class was usually divided into two parts: *lecture* and *group-work*. During the lecture, the teacher usually spoke at the front, and the students were sitting and listening. During group-work, the students formed groups based on their seats and conducted an experiment or used various science instruments, for instance, changing a pendulum's weight and initial angle to study its characteristics.

E. Questionnaires and Exam

We gathered questionnaires before the study. Below are the scales that were used as the estimation targets.

Self-efficacy: Among many scales for self-efficacy, we adopted one specifically prepared for children of similar ages [27] that consists of three items, such as, "No matter how much effort I make, I cannot learn science (reversed item)," rated on a 1-to-5 point scale. Cronbach's α was 0.71, indicating acceptable internal consistency.

Performance-goal: We adopted a scale specifically prepared for children of similar ages [27] that consists of two items, such as, "I participate in science class to outperform other students," rated on a 1-to-5 point scale. Cronbach's alpha was 0.67, indicating that the internal consistency remained acceptable.

Exam score: We gave exams during the study period that covered all three topics they studied. We averaged the scores, which ranged between 0 and 10.

F. Obtained Dataset

Behavioral data: The observed children's behaviors are quite different across the three class phases: *lecture*, *group-work*, and *free-time*. As previously discussed, we did not use any features of the *lecture* phase.

During *group-work*, children generally stayed at their desks, where they engaged in activities related to science experiments. Some worked alone, and others worked together. Some children visited other desks to check the progress of the other groups or to ask about their problems.

During *free-time*, children were often with their friends. Before the science class, many were talking with friends, and some were sitting at their own desks and waiting for class to start. After the science classes, some children gathered around the robot and interacted with it, and others briefly chatted with friends or returned to their homerooms.

We separated the data based on the above phases and used both phases for estimation purposes. We collected 235 minutes of *group-work* data and 112 minutes of *free-time* data.

Questionnaire data: Overall, we got 74 valid data samples. Some children were absent when the questionnaires were administrated, and others failed to completely fill them out even after being reminded a few times. As predicted in the literature, their exam scores are significantly correlated with self-efficacy (p=.007) and almost significantly correlated with performance goal (p=.089). We identified no significant correlations among the three personal traits.

V. EVALUATION

A. Performance

We trained the classifiers using the obtained data and searched for the best features from all the combinations of features and parameters for SVM through a grid search. We used 5-fold cross-validations to evaluate their performance.

Table 1 shows the obtained features and performances. Overall, our system achieved 73.0-74.7% accuracy. The bold fonts represent the highly contributory features. That is, removing them decreases the performance by more than 15% from this final result.

The SVM classifier achieved 73.0% self-efficacy accuracy. As we expected, the key features are the *number of surrounding people* in the group work and the *spent time around the robot.* Associated with *spent time around the robot* and the *number of surrounding people*, children were not generally alone because they often interacted with the robot, and hence these features also contributed. The *sitting time* in group-work also contributed (correlation is 0.11).

The SVM classifier achieved 73.3% performance goal accuracy. Children with a high performance goal have more *time spent alone*, as we expected. Unexpectedly, free-time features also contributed. For instance, these children have lower *number of surrounding people* values in free-time (correlation is -0.16), and more *sitting time* (0.13), possibly because they tended to stay in the room after class and work with their notebooks for a while.

The SVM classifier achieved 74.7% exam score accuracy. Children with high exam scores seemed to seriously study during the classes. *Sitting time* highly contributed (correlation is 0.20), and the *moving distance outside one's own desk* also contributed (-0.10). Thus, they did not move around much and sat for a longer time.

B. Case Studies

The estimation result provides insight about the relationship between children's behavior and their personal traits. Here we further scrutinized some children's behavior and retrieved scenes based on the contributing features for the classifiers. For self-efficacy, the *number of surrounding people* in both *free-time* and *group-work* and the *sitting time* in *group-work* were major contributory features. Fig. 4 shows scenes where a child with high self-efficacy stays with friends around the robot. She frequently interacted with it, often invited her friends to join her, and engaged with them by answering the robot's class-related quiz-style conversations.

For the performance-goal, the *number of surrounding peopl*e and the *sitting time* during *free-time* were major contributing features. Fig. 5 shows scenes where a high performance-goal child was still studying after class. Even when many children were talking near her and returning to their rooms, she continued to write down notes.

For the exam scores, the *sitting time* during *group-work* was one major contributing feature. Fig. 6 shows scenes where two children with high (solid circles) and low (dotted circles) exam scores are studying during group-work. The high exam score child seriously worked on his experiment at his desk, but the low exam score child did not join the experiment and played with his friend.

VI. Discussions

A. Implications

This study shows promise for estimating children's learning-related personal traits and suggests that we can develop a robot that supports a child's learning by adapting to individuals. For example, if a robot recognizes a child who has low self-efficacy, it should provide proactive help when the child seems to be rudderless. Otherwise, such a child is probably reluctant to get help. If a robot found a child with a high performance goal, it might elicit more competition, which would encourage that child to study even more.

Further, in a classroom, a robot might be expected to find children who need learning support, e.g., children with low performance goal or low self-efficacy. In the future, a robot might be used to increase such children's curiosity or interest in learning [25]. At the moment, it remains unknown how to effect such encouragement, and finding a way to make robot behaviors for such purposes is one future work enabled by this study.

B. Privacy Concern

Our system achieved identification, position tracking, and the estimating of personal traits of children in school, which is useful information if used appropriately. However, much discussion has focused on privacy concerns with positioning systems and our method admittedly increases privacy risks. It is important to analyze what we can know from such sensor data. Informed consent is essential from children, their parents, and teachers. They should clearly understand the potential ramifications of such studies. Our study certainly provides information for this.

In future use, the system's benefits to the detriment of privacy are important. For example, for future applications, social robots may be able to better serve children's learning if they can identify children's individual differences. We believe that social robots will offer such benefits.

C. Generalizability and Limitations

The study was conducted at a specific environment with many specific personal traits, such as culture, language, lecture style, and the robot's role/behavior. For instance, although it was conducted solely in a science room, children might behave quite differently in their homerooms. If we use the system elsewhere or in other rooms, we need to adjust such aspects as camera arrangements, since the desk arrangements will be different. Nevertheless, we believe that our study framework is valid for many different settings, if we train SVM again for different settings.

VII. Conclusions

We developed a personal trait estimation system that consists of a people tracking system using depth sensors and a person identification system using RGB cameras. The system extracts features from children's behaviors including social signals during classes and free-time and estimates their school-related personal traits using SVM classifiers. We gathered children's behaviors at a science room in an elementary school. Our system achieved 73.0-74.7% accuracy for estimations of two personal traits (*self-efficacy* and *performance goal*) and *exam score*.

Table 1 Performance of SVM classifiers

Personal traits	Perfor-mance	Features: Group-work	Features: Free-time
Self-efficacy	73.0%	**- Sitting time** **- Number of surrounding people** - Time spent alone	**- Time spent alone** - Sitting time - Number of surrounding people - Spent time around the robot
Performance goal	73.3%	- Time spent alone	**- Sitting time** **- Number of surrounding people** - Moving distance outside own desk
Exam score	74.7%	**- Sitting time** - Moving distance - Moving distance outside own desk	**- Moving distance outside own desk**

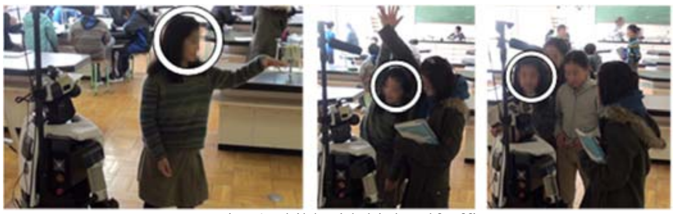

Fig. 4 Child with high self-efficacy

Fig. 5 Child with high performance goal

Fig. 6 Children with high/low exam scores

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