

# Age Estimation from Dual-Task Behavior for Comprehensive Growth Assessment of Children

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**Abstract**—This paper presents age estimation of school-age children from dual-task behavior, which is known to be affected by cognitive ability. By observing a school-age participant performing the dual-task with Kinect and other sensors, our dual-task experience system measures his/her anthropometric, kinematical, and cognitive aspects of information simultaneously. We collected observations of more than a thousand school-age children, applied regression for estimating ages from each aspect and all of them, and discussed their differences. As a result, we found that age estimation using the all aspects is the best. This fact indicates that our age estimation could be useful for comprehensive growth assessment of children.

## I. INTRODUCTION

Within the growing process of children, various body characteristics are developing with increasing age [1], [2], e.g., body height becoming taller, walking style becoming more stable and learning ability improving with age increasing. So child's age can be estimated by these features. For example, Shi et al. use the performance of physical examinations to estimate age for elementary school children [3], and Moshman [4] studies relation between cognitive development and age of children. But, a common problem in those existing studies is that they only explored one aspect of growth information, which is not sufficient information for age estimation.

In this paper, we adopt dual-task observation to overcome this problem. Dual-task, which means doing two tasks (usually combination of physical task such as walking and stepping, and cognitive task like arithmetic calculation), is originally proposed for rehabilitation of elderly people with cognitive disability, but useful for our purpose; by adopting this dual-task methodology, we can obtain anthropometric, kinematical, and cognitive features at the same time. The anthropometric feature is simply obtained from range and joint data of a participant. The kinematical and cognitive features are from performance of the physical and cognitive tasks, respectively.

We develop a data-collection system to easily and automatically record a participant's dual-task behavior, and locate it in a national science museum in Japan, so that we finally

collect more than a thousand school-age children data. Dual-task performance of each participant is subsequently quantified by various features. We estimate his/her age with both separate aspects or combination of all aspects of the features, and compare performance of them to find the best one. We then confirm that using the combination of all different aspects of features gives the best performance comparing using only one aspect. And its accuracy is less than one year. Since we collect the data from ordinary children and the number of subject is relative large, in statistical sense, our age estimation using all aspects of information could be used for comprehensive growth assessment of children.

## II. DATA COLLECTION AND FEATURES EXTRACTION

We design a system to automatically record various measurements about the participants who are performing dual task. We need to consider the way to realize automation and the method to guarantee the ethical rights of the participants. Our solution is as follows: Before each step of the procedure, guidance is displayed on the screen for participants. At the beginning of the experiment, we explain to participants that what kind of information will be recorded and ask for their agreement to use this information for research purpose. At the end, the participant is provided an opportunity again to refuse the agreement again after checking the captured data.

For dual task, we adopt stepping in place as our motor task, and use calculation of addition or subtraction between one and two digits (e.g.  $74+2=?$ ) as the cognitive task. The Microsoft Kinect sensor is used to track each participant's stepping movement of the whole body. The color image sequence, depth map sequence and the time series of 3D coordinates of the body joints are captured. Fig.1 shows out an example of these data collected from a participant. In addition to those physical measurements, features about the dual task (responding time and correctness of answer) is also recorded. Throughout the long-term exhibition in a national science museum in Japan, we collected data from from 1113 children aged from 6 to 15 years old.

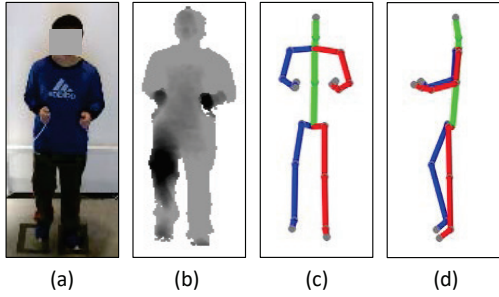


Fig. 1. Data captured by Kinect sensor. (a) color image; (b) depth map (only human region) (c) and (d) are the skeleton image from front view (X-Y plane) and lateral view (Z-Y plane)

From the collected data, we quantitatively describe three aspects of information with various features. Cognitive information which is about the performance of answering arithmetical questions, is expressed by average of answer time and correct answer ratio. As anthropometrics, we measure body height from 3D point cloud which is converted from depth map, lengths of arm span/legs calculated from 3D joint skeleton and also their ratios (e.g. ratio of length of arm span to height). Kinematical characters which describe the movement of stepping is also extracted from time series of 3D joint position. We use the speed and variability in temporal and spacial space of all the joints (except some joints at tip) and axes to describe the stepping performance.

### III. AGE ESTIMATION

#### A. Regression and evaluation method

The regression method we use for age estimation is gradient boosting regression [6] which uses additive strategy to learn basis model with forwards stage-wise fashion. Here we choose classification and regression tree (CART) as basis model (weak learner). The most important advantage of this method is that with the CART as basis model, it does not require any assumptions of linearity in the data.

We repeat 5-fold cross-validation 5 times to evaluate the regression performance. The performance of age estimation is measured by Mean Absolute Error (MAE). Given the estimated age  $\hat{a}_i^t$  and ground truth age  $a_i^t$  for the  $i^{th}$  test sample, the definition of MAE is:

$$M = \frac{1}{N^t} \sum_{i=1}^{N^t} |\hat{a}_i^t - a_i^t|,$$

where  $N^t$  the number of test samples. The reported MAE is the average of those 25 execution mentioned above. Statistical significance tests are performed using one-way analysis of variance (ANOVA) with the null hypothesis that two sets of samples are drawn from populations with the same mean.

#### B. Results and discussion

The average of MAE in table I are different with each other significantly (p-value  $\ll 0.001$ ). Observing MAE results, we find that the MAE of the anthropometric aspect feature is

TABLE I  
PERFORMANCE COMPARISON OF DIFFERENT FEATURES

Aspects	MAE[years]
Cognitive	1.57
Anthropometric	0.90
Kinematical	1.38
Combination (in feature level)	0.85

smallest, which means the anthropometric aspect is the most effective for age estimation. The kinematical aspect is the secondly effective, while the cognitive one is the worst.

When concatenating all the aspects of features, the MAE decreases statistically significantly to 0.85 years. This means combination features have the most discriminative ability to describe growth condition of children comparing with single aspect of information. The improvement is not so large compared with that from the anthropometric features, which means that the two other aspects do not provide much contribution. It might be because they do not develop with age as fast as anthropometry do. On the other hand, the kinematical and cognitive aspects show measurable contribution (MAE is much smaller than chance level of 2.5 years) for age estimation.

### IV. CONCLUSION

Motivated by the fact that dual-task behavior is useful for evaluating cognitive ability, we investigate age estimation performance using dual-task observation. Since the dual-task behavior is captured by Microsoft Kinect, we can obtain anthropometric and kinematical features as well as the cognitive one, so that we can investigate which feature and which combination gives the best performance for the age estimation. The experiment results using more than a thousand school-age children data revealed that using all the features gives the best performance and its accuracy is less than one year. Considering the accuracy under the experiments with quite large number of ordinary school-age participants, our age estimation can be regarded as a good measure for assessing the children comprehensive growth.

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