Identification of human kinematics and marker arrangement model based on gradient estimation from coarsely sampled motion capture data

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1. Introduction

Optical motion capture technology is useful for many human-oriented applications such as animation rendering, sports training, ergonomic designs, etc. A mathematical toolbox for robot kinematics computation is available for the analysis of motion data. It requires a model of kinematics and marker arrangement of the captured subject in order to reproduce its original motion from measured loci of the markers. However, it is almost impossible to make it accurately through direct measurements of body parts. Some techniques [1][2][3] to identify the model from the measured loci of the markers have been proposed. A remaining problem that has to be solved is of its heavy computation cost in the non-linear regression process that handles a vast amount of data.

This paper proposes a method to reduce the cost by estimating gradient direction in error minimization from coarsely sampled data. Stochastic sampling of the data at only one time frame equalizes the estimation variance in the time domain so that the accuracy is not sacrificed.

2. Model identification with dual-phase least square error approach

The original motion of the captured subject can be reproduced from measured loci of retro-reflective markers attached to the subject's body through the inverse kinematics (IK) computation [4] if the kinematics model with marker arrangement is available. It is not trivial how to acquire the model beforehand. When considering to identify the model from the measured markers, it would be a chicken-and-egg problem.

Another difficulty lies in its ill-posedness. Several possibilities for correcting the model exist with respect to the given set of marker positions. Namely, the error of marker positions can be cancelled by adjusting whichever the link length or the relative marker positions attached to the link in many situations as Fig.1 depicts.

The idea is to estimate the most likely combination of the model and the motion simultaneously in a cyclic way. The error function is defined as

$$E = \sum_{j=0}^{N_{\mathrm{F}}} \sum_{i=1}^{N_{\mathrm{M}}} \left\| \tilde{\boldsymbol{p}}_{\mathrm{M}i,j} - \boldsymbol{f}\left(\tilde{\boldsymbol{p}}_{\mathrm{M}i,j}, \boldsymbol{\kappa}, \{{}^{Li}\boldsymbol{p}_{\mathrm{M}i}\}, \boldsymbol{q}_j\right) \right\|^2, \quad (1)$$

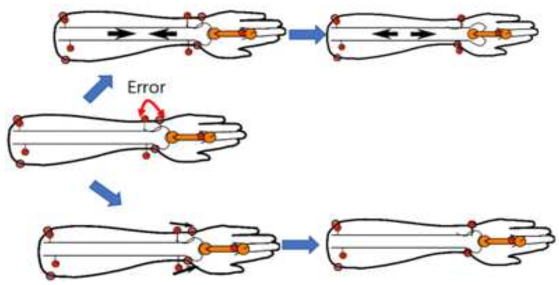

図 1　Two methods to adjust kinematics model

where $\tilde{\boldsymbol{p}}_{\mathrm{M}i,j}$ represents the measured position of the i-th marker at the j-th frame, $\boldsymbol{f}\left(\tilde{\boldsymbol{p}}_{\mathrm{M}i,j}, \boldsymbol{\kappa}, \{{}^{Li}\boldsymbol{p}_{\mathrm{M}i}\}, \boldsymbol{q}_j\right)$ represents the estimated position of the i-th marker via the forward kinematics (FK), $\boldsymbol{q}_j$ represents the joints configuration at the j-th frame, $\boldsymbol{\kappa} \in \mathbb{R}^{N_{\mathrm{K}}}$ and $\{{}^{Li}\boldsymbol{p}_{\mathrm{M}i}\} \in \mathbb{R}^{N_{\mathrm{M}} \times 3}$ are kinematics model parameters of links and relative positions of markers attached to the link, respectively. N_{K}, N_{M} and N_{F} are the number of kinematic parameters, markers and data frames, respectively.

IK finds $\boldsymbol{q}_j$ that minimizes E with respect to the given $\boldsymbol{\kappa}$ and $\{{}^{Li}\boldsymbol{p}_{\mathrm{M}i}\}$. The model identification is to find a combination of $\boldsymbol{\kappa}$ and $\{{}^{Li}\boldsymbol{p}_{\mathrm{M}i}\}$ that minimizes E with the best associated $\boldsymbol{q}_j$. Obviously, the latter includes the former inside, so that it can be implemented as a dual-phase least square error and solved by a non-linear minimization method such as the optimal gradient method.

3. Numerical gradient estimation from coarsely sampled data

The gradient direction can be estimated by numerical differentiation of E. In order to compute E once for the given $\boldsymbol{\kappa}$ and $\{{}^{Li}\boldsymbol{p}_{\mathrm{M}i}\}$, it is required to solve IK N_{F} times, which is the source of the heavy computation cost. An idea to reduce the cost is to approximate E from coarsely sampled data. The number and intervals of samples have to be discussed. The authors examined the following three methods: (1) 1/10 samples of the total with even intervals, (2) 1/10 samples of the total with random intervals, and (3) only one randomly-picked sample. The computation process is described in Algorithm 1.

Algorithm 1 Simultaneously identify a human's kinematics and marker arrangement model

Input: csv file from motion capture system, initial kinematics model $\boldsymbol{\theta} = \{\boldsymbol{\kappa}, \{{}^{Li}\boldsymbol{p}_{\mathrm{M}i}\}\}, \boldsymbol{\theta} = [\theta_1, \theta_2, \cdots, \theta_{N_{\mathrm{K}}+3N_{\mathrm{M}}}]$
Output: modified kinematics model $\boldsymbol{\theta} \in \{\boldsymbol{\kappa}, \{{}^{Li}\boldsymbol{p}_{\mathrm{M}i}\}\}$

for $k \in [1, \text{iteration steps}]$ **do**
  for $j \in [1, N_{\mathrm{F}}]$ **do**
    for $i \in [1, N_{\mathrm{K}} + 3N_{\mathrm{M}}]$ **do**
      modify $\theta_i := \theta_i + \Delta$
      IK/FK and calculate cost function
      accumulate gradient $\frac{\mathrm{d}E(\boldsymbol{\theta})}{\mathrm{d}\theta_i} += \frac{\mathrm{d}E(\boldsymbol{\theta})}{\mathrm{d}\theta_i}$
      modify $\theta_i := \theta_i - \Delta$
    end for
  end for
  Update model $\boldsymbol{\theta} := \boldsymbol{\theta} - \alpha \frac{\mathrm{d}E(\boldsymbol{\theta})}{\mathrm{d}\boldsymbol{\theta} \cdot N_{\mathrm{F}}}$
end for

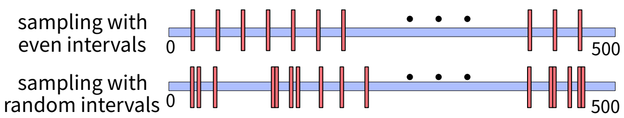

図 2 Two ways of course sampling of motion capture data with even and random intervals

表 1 Time consumption of all sampling method

Method	sampled frames	loops	Time (s)
stochastic	1	100	15.52
stochastic	1	300	44.51
stochastic	1	500	75.99
even intervals	50	100	690.66
random intervals	50	100	711.74
batch	500	100	6758.98

4. Evaluation

The above three methods were examined and compared. The skeleton-marker model of the human body was made of 48 DOF and 22 rigid links with the number of markers $N_{\mathrm{F}} = 39$ and the number of kinematic parameters $N_{\mathrm{K}} = 30$. Five-second record of motion data at 100 Hz of sampling rate was used for the identification. The time consumption for the optimization is shown in Table 1.

The error of the marker positions at each time frame is shown in Fig.3, and the error accumulation in the time domain is shown in Fig.4.

The method using the aggregate data (500 frames) took more than 100 minutes to complete. Obviously, the methods using 1/10 samples reduced the computation time also to 1/10 with respect to the fixed iteration time step 100. The two methods showed almost the same performance in terms of accuracy. Surprisingly, the accuracy by the method with only one random sampling was almost the same, while the computation time was significantly reduced with respect to the same iteration steps. The accuracy was improved by increasing iteration steps, and the computation time was still even lower than the other methods with 500 iterations.

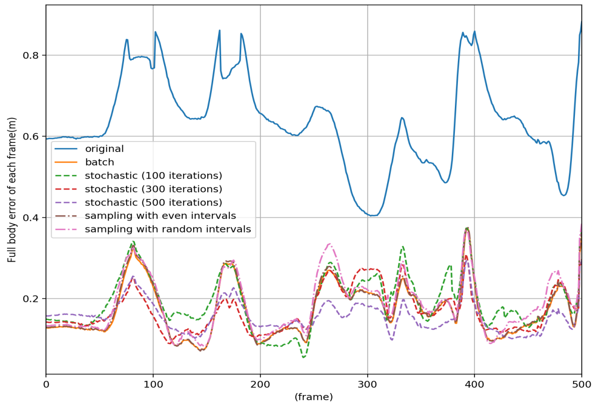

図 3 Comparison of the error of IK with the kinematic and marker arrangement model identified by the proposed methods

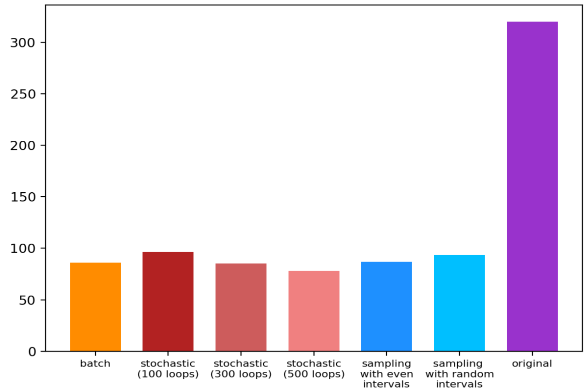

図 4 Error accumulation in the time domain of all modified models

5. Conclusion

This paper proposed a method to identify a human's kinematics and marker arrangement model simultaneously. The algorithm with the stochastic sampling technique significantly reduced the computation cost and showed better accuracy than the other sampling methods.

References

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