Study of Periodic Segments in Analysis of the Skills in Periodic Motions Using Bayesian Networks

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Abstract

In this study, the motions involved in hula hooping were divided into several chronological segments, and a method for determining the skills involved in each segment developed. A significant number of the actions we perform every day, such as walking and running, involves periodic operations. These actions are learned early in childhood and, in later life, we go through the motions unaware of the component actions. However, when it becomes necessary to reacquire these talents through rehabilitation or other means, a considerable amount of effort is subsequently required through repeated trial and error before we can efficiently perform them once more. We have developed an algorithm that can chronologically and quantitatively represent the skills involved in these periodic behaviours. This paper outlines the construction of a Bayesian networks model used for analysis, and presents information on the number of segments, representation of the skills involved in a motion/action when there is variance in the position of a segment, and the reliability of those skills.

1 Introduction

Human actions involve a significant number of periodic phases. These motions, rather than being performed according to active thoughts in the brain, are executed through central pattern generators in the spinal cord (CPG). CPG is making those rhythm of movements [1] [2]. Someone's first experience move, cerebral cortex plan and a command is executed. If movement is repeated, a spine will memorize a rhythm of operation. As a result, teaching any such behaviour to others is difficult because the conscious mind is not involved in the performance of the action. Consequently, providing effective guidance during physical rehabilitation, while playing sports, etc., can be a problem. Conventionally, when modelling actions or motions, a kinematic model is customarily used for motion analysis Delp et al. simulated the movement of body parts and action of muscles throughout the human body using a kinematics model [3]. Nakamura et al. created a whole body muscle model [4] that can estimate and display muscular activity in real time. And it can use for discriminate efficient motion or not. However, the construction of a kinematic model requires large-scale measuring equipment, and making use of this in actual rehabilitation and sports-related instances is quite difficult. This problem can be addressed without using physical models by identifying the parts that need to be measured in order to construct the model. In this study, to determine the success of the motion, we utilised the easy-to-understand activity of hula hooping. A number of studies have been conducted of the actions involved in hula hooping using kinematic analysis techniques [5]. Kakehashi et.al. make musculo-skeletal humanoid robot which can hula hoop [6]. However, very little quantitative analysis has been performed. We used an algorithm that utilises the discriminant model announced at SSS2014 and Bayesian networks in our study. This method has the advantage of being subject to quantitative analysis. For this study, in order to examine the changes in reliability resulting from the periodic segments and positioning of those periodic segments, models that used different phases of two, four, and eight segments were evaluated by quantitative and qualitative assessment.

2 Method of Building the Models

There are two steps to the analysis presented in this paper as shown in Figure 1. First, we build a discrimination model from data for the motions of a skilled subject and an unskilled subject. Using the criterion of the distinction efficiency, we determine important parameters that can be used to classify skilled and unskilled subjects. We then presume how many movement required each part quantitatively employing the Bayesian-network-based method proposed in this paper.

The Bayesian network builds a causation model from the marginal probability and joint probability of several phenomena to calculate the probability of the desired phenomenon under a certain condition. As an example
from another field, Bayesian estimation can discriminate spam email by filtering combinations and frequency of words in emails [7]. It is difficult to conduct a full search because of the computational cost. Moreover, relevance is incorrectly detected between the same parameters. To eliminate incorrect detections, we limit the search to parent-node candidates. Thus, we use the heuristic K2 algorithm [8] to construct the network. The K2 algorithm is a greedy algorithm that is used to search for combinations of nodes.

Prior to constructing the network, the candidates are restricted to parent nodes. The partial solution with the best score at each stage of the calculation is selected to build the network in alignment with the actual condition. Constructing a final solution from the combination of partial solutions is less computationally expensive than conducting a full search.

The procedure for constructing the network is summarized as follows.

1. **Selection of a parent node**
   We select parent-node candidates using prior knowledge.

2. **Creation of a graph**
   We add the parent node that serves as a candidate for one child node, and create a graph.

3. **Calculation of a score based on an evaluation index**
   We determine and evaluate the parameters of the graph.

4. **Evaluation of a parent-node candidate**
   We define a parent node as that for which the evaluation exceeds a front graph.

5. **Confirmation of the graph of a child node**
   When evaluation stops becoming high, even if the candidate who adds as a parent node.
The network is built by repeating steps 1–5 for all nodes. In this study, the K2 metric [9] expressed by formulas 1 and 2 was used as the network evaluation value. \( N \) is the number of all nodes, \( L \) is the total number of states assumed by child nodes, and \( N_{jk} \) is the number when parent nodes assume a \( j \) state and child nodes assume a \( k \) state.

\[
K2Metric = \prod_{i=1}^{N} \prod_{j=1}^{M} \frac{(L-1)!}{(N_{ij} + L-1)!} \prod_{k=1}^{L} N_{ijk}! \tag{1}
\]

\[
N_{ij} = \prod_{k=1}^{L} N_{ijk}! \tag{2}
\]

There are three benefits to using Bayesian networks.

a) A Bayesian network builds a statistical model reflecting factors that may be omitted or oversimplified in physical models.

b) Once a model has been built, there is no need to modify it every time a condition changes.

c) The method not only derives a result from a cause, but also a cause from a result.

We define the range as very back (0%) to very front (100%) in measurement. This figure denotes the present position in the moving range of measurement time. For example, the position of the right shoulder is at 80% of its full range. These levels are used as node thresholds to create nodes for the Bayesian network when building the causal sequence model shown in Fig. 2(a). The graph at the lower left is image of correspondence of analog data and threshold level. The connections in Fig. 2(a) denote causality between each position (each color). We divide the amount of movement in each body part into five levels, as shown in Fig. 2(b). In this way, the effects of different conditions can be determined for each phase of using the hula hoop. Using 16 parameters, each divided into five levels, we obtain a model consisting of 80 nodes.

In order to determine the skills involved in a particular motion, the periodic segments of a distinctive action were found by constructing a Bayesian network that divided each phase into a child node. The periodic segments that exist when hula hooping are divided depending on the position of the centre of the hula hoop relative to the centre of the body. The segmenting method is shown in the ten patterns presented in Figure 3.

3 Experiments

Experiments were conducted to apply the proposed algorithm to actual movement. The goal was to determine important body parts at each phase of rotation, and to build a model that represents the relationship between each rotation phase and the position of body parts and evaluate the models by quantitative and qualitative assessment. Four expert subjects participated in the experiment. They turn the hula hoop clockwise on the right foot. We defined an expert to be a subject who was able to use a hula hoop for 10 s. We measured the positions of 25 points on the subject’s body and six points on the hula hoop, as shown in Figs. 4 and 5. Table 2 shows the measurement condition.

We calculated the middle point and the center of gravity of each body part from the three-dimensional position acquired by a motion capture device. For example, waist was estimated from gravity center of quadrangle of a14, a15, a16, a17.

In the periodic motions, there is a point at which switched features Thus, we built a discriminant model and a Bayesian network that represent the relationship between each rotation phase and bodypart position. We determined the center position of the hula hoop by gravity center of a hexagon of six marker points (a26 - a31) on hula hoop. This enabled us to divide the motion into the phases shown in Fig. 3. Blue point is time-series point of center position of the hula hoop. For each one divided phases, we have built a model. We then constructed a Bayesian network model using the following three methods of division. We verify the suitableness of each divided model.

i) 4 types two-part model: The frontal/sagittal model and right/left model

ii) 4 types four-part model: Each 90° about the center axis. By shifting the start point by each 15°.

iii) 2 types eight-part model: Each 45° about the center axis.

4 Result and Discussion

After determining segmentation with various phases for a characteristic action using the Bayesian network, with consideration for the descriptive function, a precise examination was conducted considering the network's objective functions and their relation to the segmentation. The results are shown in Figure 6.

When two phases were used for right and left, the overall accuracy was low. Further, no change in accuracy was found as a result of a different starting position being used for the phases, even when four and eight segments were introduced. While there is a difference in the major characteristic of this action, that is, a back-and-forth movement, because a clear difference is not generated in the action in a left and right direction, the results of the estimation accuracy of the model can be said to match the action very well.
Fig. 3 Division of rotation phase according to the position of a hula hoop.
Table 2 Parent nodes of motion in each rotation phase Pattern 9 and Pattern 10

<table>
<thead>
<tr>
<th>Pattern 9</th>
<th>Primary parent node</th>
<th>Secondary parent node</th>
<th>Pattern 10</th>
<th>Primary parent node</th>
<th>Secondary parent node</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1</td>
<td>waistZ8</td>
<td>R_wristX2</td>
<td>E1</td>
<td>waistZ8</td>
<td>L_shoulderX2</td>
</tr>
<tr>
<td>A2</td>
<td>R_wristX2</td>
<td>L_shoulderX2</td>
<td>E2</td>
<td>R_wristX2</td>
<td>waistZ6</td>
</tr>
<tr>
<td>B1</td>
<td>R_wristX4</td>
<td>waistZ8</td>
<td>F1</td>
<td>R_shoulderX6</td>
<td>R_O_kneeZ4</td>
</tr>
<tr>
<td>B2</td>
<td>R_O_kneeZ4</td>
<td>R_shoulderX8</td>
<td>F2</td>
<td>R_O_kneeZ6</td>
<td>R_shoulderX8</td>
</tr>
<tr>
<td>C1</td>
<td>waistX4</td>
<td>waistX2</td>
<td>G1</td>
<td>R_O_kneeX2</td>
<td>L_wristX6</td>
</tr>
<tr>
<td>C2</td>
<td>L_O_kneeX4</td>
<td>L_O_kneeX2</td>
<td>G2</td>
<td>R_shoulderX6</td>
<td>waistX2</td>
</tr>
<tr>
<td>D1</td>
<td>R_shoulderX6</td>
<td>waistX4</td>
<td>H1</td>
<td>R_O_elbowX4</td>
<td>L_O_kneeX8</td>
</tr>
<tr>
<td>D2</td>
<td>R_O_kneeZ4</td>
<td>R_shoulderX4</td>
<td>H2</td>
<td>R_O_kneeX6</td>
<td>R_wristX2</td>
</tr>
</tbody>
</table>
Table 1  Measurement condition

| marker | 31points(Subject : 25points  
| Walker : 6points) |
| Measurement | Hula hoop |
| operation | capture rate | 100[Hz] |
| Measurement | time | 15[s] |
| Subject | Healthy male in his(her) twenty |

There is not much different in meaning among four divided models, and among eight models. In addition, the accuracy does not vary significantly as a result of the divided into four and eight segments. In general eight divided model is harder then four divided model to discriminate the phases. So we investigated about the model which dividing the motion into eight parts, Pattern9 and Pattern10 in detail.

We show the parent nodes of motion in each rotation phase of Pattern 9 and Pattern 10 in Table1. There are same parent node among Pattern 9 and Pattern 10 like as A1 and E1, A2 and E2 because these phases are superimposed half of phase. From these same parent node, we can discover that more details about skills of hula hoop each 22.5° timing. In regards to skills of hula hoop, it is said that it is important how to move waist when hula hoop is in front of body in general. However knee nodes are parent node in six phase. So we can say the skill of hula hoop is not only how to move waist but also how to use knee.

5 Conclusions

In this study, a Bayesian networks model was constructed and examined from the standpoint of periodic segments. In addition, the reliability of the skills representing an action when there is variance in the positioning of those periodic segments was also examined. The results obtained indicate that by using the estimation accuracy of the algorithm and a method for checking the reliability of the model, a model which matches the motions involved in an actual behaviour or action can be built. In this experiment, in order to discover important parts from the whole body, we used the motion capture suit, and conducted three-dimensional movement analysis. However, in the future It can simplify drastically experiment environment, such as camera measurement from one direction where the part discovered when actually measuring skill level.

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