유아의 동작 교육을 위한 실루엣 기반 동작 추정

Silhouette-based Motion Estimation for Movement Education of Young Children

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요약

동작은 유아의 신체적, 사회적, 인지적 발달에 매우 중요한 요소이다. 본 논문에서는 유아의 신체에 적절한 동작 추정 방법을 제안한다. 본 논문에서는 동작교육에 필요한 동작 중에서 걷기, 뛰기, 앙감질의 이동 동작과 구부리기, 뻗기, 균형잡기, 회전하기의 비이동 동작을 대상으로 한다. 제안된 시스템은 두 대의 카메라에서 획득된 프레임에서 조명 보정, 배경 제거, 모폴로지 실행 등의 과정을 통해 실루엣을 추출한다. 실루엣 특징으로 면적, 가로세로 비율, 발의 위치, 7개의 Hu moments를 사용한다. 또한 지역 특징으로 실루엣을 5×3으로 나누어 각 영역의 면적과 움직임을 사용한다. 동작 추정을 위해서, 추출된 특징에 확률 전파를 적용하였다. 본 논문에서 제안된 알고리즘은 마커없이 유아들의 기본 동작을 추정함으로써 동작 교육을 위한 가상 학습공간에서 실감형 인터페이스로 사용될 수 있는 가능성을 보여주고 있다.

■ 중심어 : | 실루엣 | 동작 추정 | 확률 전파 | 동작 교육 |

Abstract

Movements are a critical ability to young children's whole development, including physical, social/emotional, and cognitive development. This paper proposes the method to estimate movements suitable for young children's body conditions. The proposed method extracts a silhouette in each frame of videos that are obtained by deploying two video cameras by compensating illuminations, removing background and conducting morphology operations. And we extract silhouette feature values: an area, the ratio of length to width, the lowest foot position, and 7 Hu moments. Also, the area and movements of sub-area are used as local features. For motion estimation, we used probability propagation of the features extracted from the front and side frames. The proposed estimation algorithm is demonstrated for seven movements, walking, jumping, hopping, bending, stretching, balancing, and turning.

■ keyword : | Silhouette | Motion Estimation | Density Propagation | Movement Education |

I. Introduction

Movements are a critical ability to young children's whole development, including physical, social/emotional, and cognitive development. It is obvious that movement contributes in numerous ways

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to physical development of young children. Active physical movements foster young children's gross motor skills and their physical fitness which allows to get the balance between calories consumed and calories burned. The ability to move well also makes children have feelings of self-confidence and allows them to explore their surroundings and the objects in them actively. Through such active exploration, young children acquire information and knowledge. Laban has shown that movement is the young children's preferred mode of learning, and that lessons that are physically experienced have more immediate and longer-lasting impact [11].

With many benefits to be garnered from movement, young children deserve the opportunity to get an appropriate movement instruction to refine and expand their movement skills. Early childhood professionals recommend that planned movement activities are daily offered to young children in early childhood program. However, daily movement activities are seldom provided in many early childhood educational settings because of the availability of space and equipment, and even regional weather. These are physical factors that restrict the movement instruction to limited manner. An alternative to overcome these physical factors is to use virtual reality environment by computers. To utilize movement instruction under the virtual environment using computers, it is an essential factor to estimate young children's movements. However, studies of movement estimation have targeted only adults thus far.

At the early stage, the perception of motions has been made by adhering markers on one's joints (wrist, elbow, shoulder, belly button, knee, foot, etc.). For such marker methods, however, a user has to wear data gloves or a magnetic sensor, which disturbs convenience in interacting between the user and the concerned computer. In particular, this method disturbs the convenience for young children whom this paper targeted. Markers also can be covered by user's movements; therefore, follow-up data handling is essential. To handle it as fast as possible, it can be applied to real time systems through dispersed handling, but, quite a large capital is necessary to do so. Hence, a current real time movement collection system is sold at high price. For this reason, a system through which young children's natural movements can be analyzed without markers is needed. An analysis of natural movements refers to perceive person's movements from the images acquired by video cameras.

Most motion estimation methods have used various features and models. Mittal *et. al* found out body location using a likelihood function, and presented a method to solve the overlapping problem of various people in one camera [15]. However, only person's configuration can be found within the image, not movement's estimation. Rosenhahn *et. al* perceived movements using a level set function [17]. They showed the excellence of silhouette-based method in comparison with motion capturing equipment-based method in terms of silhouette based movement perceiving method. However, they estimated only upper body and showed the perception of only several limited movements. Ren *et. al* proposed a method for animation by perceiving East-Coast Dance movements [16]. However, they used motion capturing data equipment for database building, and the movements were perceived in the limited space, that is, on the foothold. Kehl *et. al* perceived person's movements by establishing a VR space [14]. They perceived person's movements in limited space. They, however, perceived only the direction pointed out by hand, not whole body movements. The researches so far have drawbacks in that they perceived only partial movements, space was limited, and high priced equipment was used.

In this paper, we propose the method to estimate movements suitable for young children's body conditions. The proposed system estimates young children motions using silhouettes captured by two cameras placed at the front and one side of the human body. This paper pursues to supplement the drawback that a silhouette cannot perceive detailed information of movements by extracting features from the silhouette targeting young children. This paper seeks to estimate movements using global features including an area, the ratio of width to length, the lowest foot position, 7 *Hu* moments, and local features including area and movements on each part obtained by dividing a silhouette by 5×3. Since each motion contains continuous frames, we can make a dynamic model by computing relations of silhouettes between adjacent frames. Then, the system computes density estimation based on the extracted silhouettes.

II. Movements in movement education

1. Movement education

The instructional methods used in movement education for young children can be classified into a physical approach, a dramatic approach, and an integrated approach [13]. The physical approach is a method to search and experiment fundamental movements focused on fundamental factors of movements. The dramatic method is to make young children express movements by dramatizing virtual situations or behaviors. The integrated approach is a method to educate young children by integrating the physical approach and the dramatic approach.

Since the purpose of this paper is to estimate young children's movements, therefore, we investigates the movement education demonstrated by the physical approach [12]. Table 1 shows some examples of movement activities for non-locomotive and locomotive skills which are suggested in the early childhood activity resource book published by the Korean Ministry of Education.

Table 1. Movement activities in the early childhood activity resource book

Movements	Examples
Bending	Bending and unfolding by drum
Stretching	Holding a rubber string and lifting up two arms
Balancing	Stepping on one block by one foot and then stepping on other block by the other foot
Turning	Turning by remote control
Pushing	Holding a partner' s hands and pushing them
Stopping	Running and stopping by flag signal
Crawling	Crawling into a tunnel
Walking	Walking in order
Hopping	Jumping and hopping
Jumping	Jumping a string line on the ground
Climbing	Climbing and going over a vaulting horse
Skipping	Skipping by maracas

In the existing education setting, classes consist of education for mostly one movement. Thus, new teaching content is needed, and corresponding class preparation has to be made; in this context, movement education is biased toward only some movements. In the non-moving motions, balancing and stopping, and in the moving motions, walking, and jumping account for 50% of the concerned education, respectively. The perception of young children's movements using a computer can be used as interface in the virtual learning space with various themes, and young children can have experience with various movements at a time. Based on the perception of young children's movements, the development of a movement educational program using a computer is possible.

2. Fundamental movements

The contents of movement education contain the fundamental movements that perceive time, space, weight, and current by using each part of the body and the applied movement which includes rhythmical movements and creative movements.

Fundamental movements are classified into non-locomotor and locomotor. Non-locomotor is a movement by fixing a person's body in one place without moving the body. It can be conducted at a time by the whole body, or can be conducted by parts of human body. Precise non-moving motion helps human form proper posture, and foster body flexibility and smoothness in self-space; thus, this motion is always necessary in our everyday lives. Non-locomotor refers to the motion making two body parts approach each other , and the following can be included in the non-locomotor: bending, stretching, twisting, turning, swinging, tumbling, balancing, avoiding, pushing, pulling, standing on one's hands, and stopping.

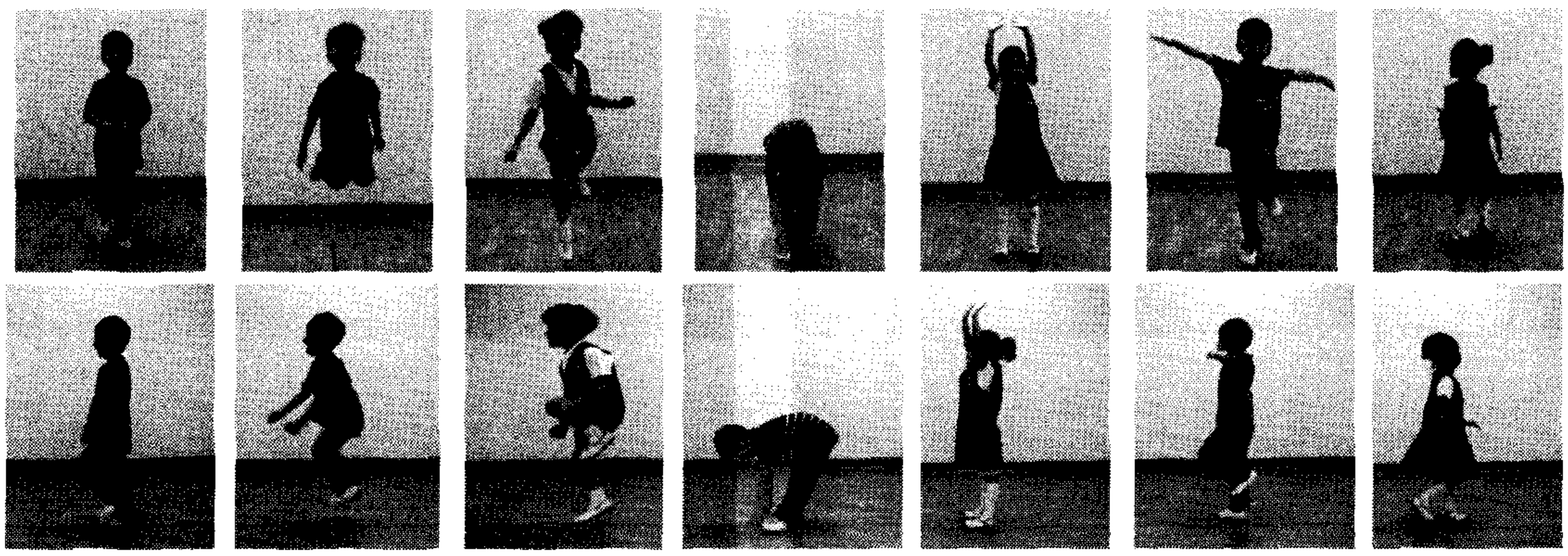
Bending is to make two close body parts approach one another through bending movement. That is, bending is to bend one's neck, waist, elbow, knee, wrist, ankle, etc: examples include bending towards one's side, and passing through under the fence. Stretching is to stretch various parts of human body vertically or horizontally: examples include stretching one's body from a bending state, passing through a tube with two arms stretched, and so on. Balancing can be conducted in a static state to support the center of body, or can be carried out while one is moving. Balancing in the static state is called static balancing, and balancing in a moving state, such as walking on the balance beam is called dynamic balancing. For example, balancing includes walking with tip toes, seesawing, and walking carrying a red bean pouch. Turning is a subsequent movement turning the whole body centered on the vertical or horizontal axis, while twisting is to twist some part of human body: example includes looking around like a turning spinning top, turning half a circle, and so forth.

Locomotor is to change the position of one's body in the space, that is, locomotor means the movement off the floor/ground, while one changes his/her body position in the space. Since the experience of the moving motion can provide the sense of rhythm to young children, it is effective to drawing creative movements in the future. Locomotor includes crawling, walking, running, hopping, jumping, sliding, jumping over, skipping, etc.

Walking is a movement moving one's weight from one leg to the other leg. As one maintains contacts with floor or ground, one changes his or her weight from one tip toes to another foot's heel. Examples can be walking to music, and walking by making various arm shapes. Jumping is a movement to jump with two one foot or two feet in the air, and get down with one foot. Examples of jumping can be a long jump, and jumping down from a high place. Hopping is the rhythmical movement landing with the same foot after one pushes up one foot with weight from the ground or floor. Examples of hopping can be hopping from a certain distance, and hopping with changes of feet.

Table 2. Seven movements for movement education

Movements		Explanation
W	Walking	Shifting weight from one leg to the other
J	Jumping	Standing jump with two legs
H	Hopping	Standing jump with one leg
Be	Bending	Bending forward keeping knee straight
S	Stretching	Extending two arms straight up
Ba	Balancing	Extending both arms horizontally and stand on one foot
T	Turning	Turning horizontally



(a) walking(W) (b) jumping(J) (c) hopping(H) (d) bending(Be) (e) stretching(S) (f) balancing(Ba) (g) turning(T)

Fig. 1 Movements for movement education : The top row shows the front view and the bottom the right-side view

This paper chose locomotive skills, such as walking, jumping, and hopping, and non-locomotive skills, such as bending, stretching, balancing, and turning, in the movement education. Of the locomotive skills, walking and jumping are taught greatly, while hopping has barely been taught in the existing movement education courses of early childhood. Of the non-locomotive skills, balancing has been mainly taught, while other skills have hardly been taught. The movements used in the system in this research are defined in Table 2. The top row of Fig. 1 shows the front view of movements, and the bottom row of [Fig. 1] exhibits the side view of movements.

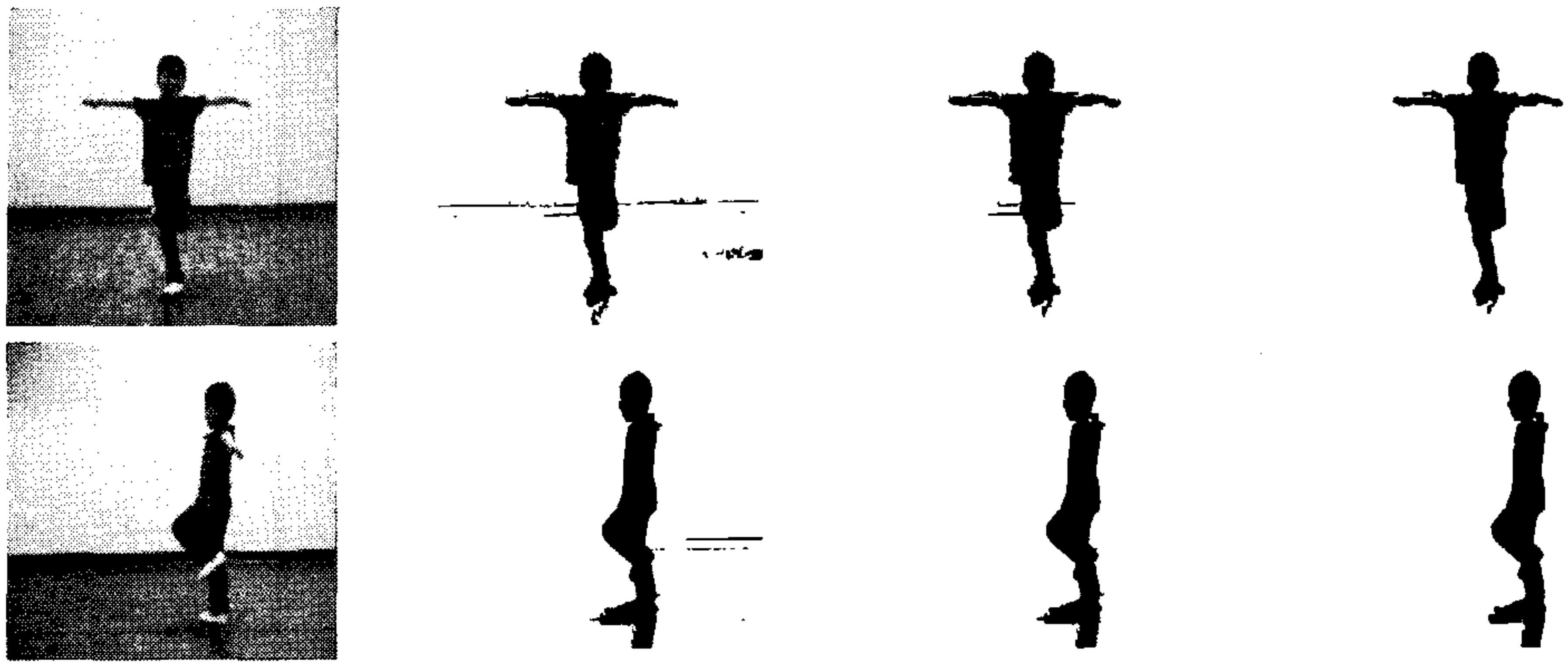
III. Silhouette feature extraction

1. Silhouette extraction

To estimate a human motion, we use silhouettes in video image frames taken by two fixed cameras (Fig. 2(a)). To extract silhouettes of a moving person, the proposed system conducts background subtraction using the adaptive background model, which uses the mean and standard deviation of the background [18]. Whenever a new frame arrives, a change in pixel intensity is computed using a Mahalanobis distance to classify background or foreground (a moving person). The evaluated distance is compared to a difference threshold previously observed from the sequence of images. If a pixel is classified as background, the adaptive background model is updated with the pixel. After background subtraction, an image frame is a semantically binary image consisting of foreground pixels and background (black) pixels [Fig. 2](b).

Such a binary image is grouped according to connected foreground pixels and segmented regions. Then the labeled connected components are filtered out depending on the bounding box of the region by removing noise-like regions and non-human body-like regions as follows:

- regions which are too long for a side of the bounding box,
- regions having small areas,
- regions having a small value of elongatedness, $\frac{\text{a shorter side of the region}}{\text{a longer side of the bounding box}}$ and
- regions having a small value of compactness $\frac{\text{area of the region}}{\text{area of the bounding box}}$



(a) Input video frame (b) Background subtraction (c) Candidate silhouette (d) Final silhouette

Fig. 2 Silhouette extraction : the upper row shows the front image and the bottom row the side image.

The above criteria provide a set of candidate silhouette areas without scanning all possible aspects ratios and the possible positions into binary segment areas. This improvement leads to improved precision in terms of locating silhouettes and helps to segment silhouettes from the background, especially when parts of the surrounding background have a motion. [Fig. 2](c) shows a silhouette by connecting detected foreground pixels in [Fig. 2](b).

In general, silhouettes are sensitive in pixel level. To reduce such sensitivity, we apply morphological operators to the binarized image. Using erosion and dilation operators iteratively make the silhouette smooth. [Fig. 2](d) shows the smoothed silhouette by using two pairs of two morphological operators.

2. Feature extraction

The silhouette features refer to features that represent characteristics of the extracted silhouette in a static frame. To represent a full-body silhouette as global features, we use an area of the silhouette (*a*), the ratio of width and height (*r*), and the lowest foot position (*f*).

We also compute *Hu* moments, which are useful features for shape-based analysis. *Hu* moments are especially good for analysis of linear transformation; thus they are invariant to scaling, translation, rotation and reflection. We compute seven *Hu* moments ($h_{1...7}$) from a silhouette [6].

Such global features, however, are subject to a high degree of transformation because the method is affected by changes in posture and lighting conditions. Therefore, we compute local features in 5×3 sub-areas ($s_{1...15}$), which are achieved by dividing the silhouette [Fig. 3].

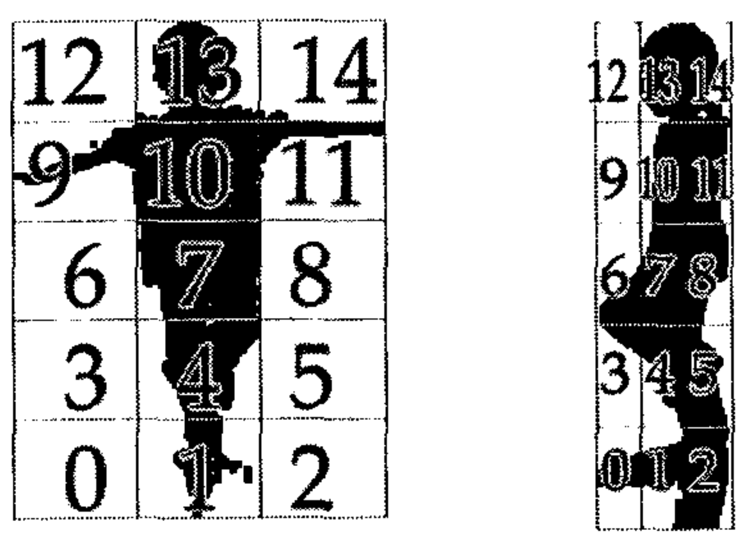


Fig. 3 Sub-silhouette areas

While, in general, the heights of babies are four times the height of their heads and those of 12-year-old children are six times and then adults

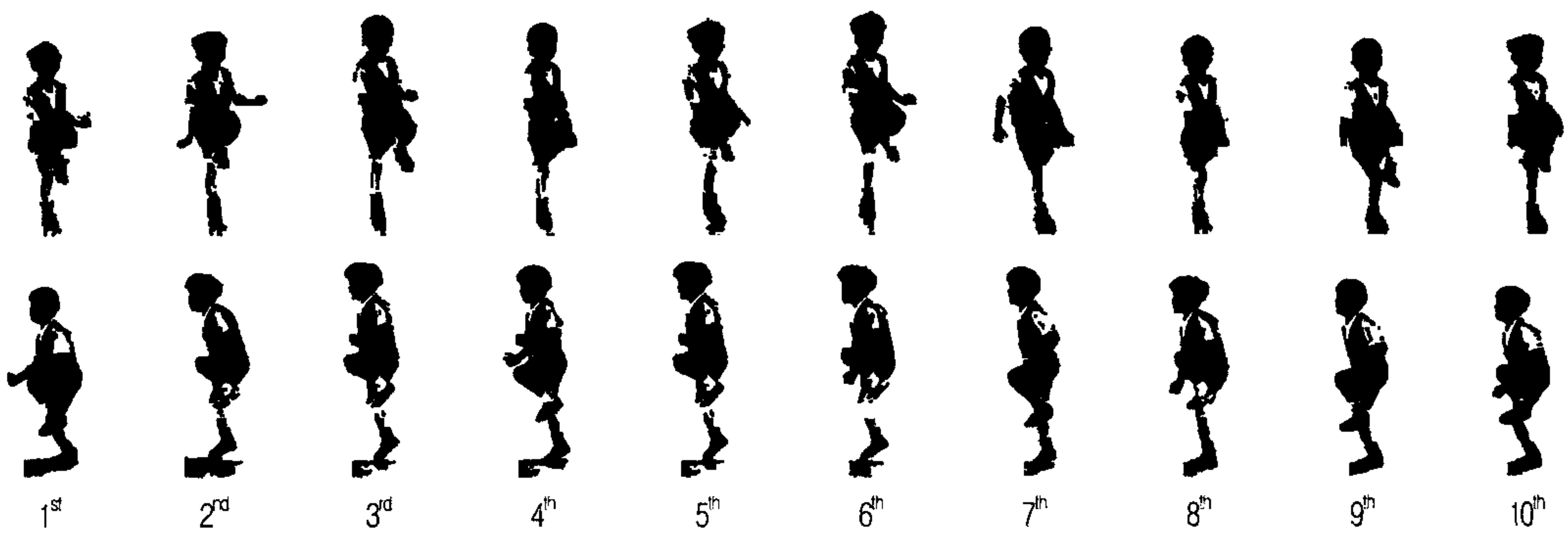


Fig. 4 Movement sequences if hopping(H) : the top and bottom rows represent the silhouettes captured by cameras of at the front and one side view, respectively.

eight times, those of five-year-old or six-year-old children are usually five times. In two cameras, two sets of 25 features are calculated on each incoming frame set:

$$x_n = \{a, r, f, h_1, \ldots, h_7, s_1, \ldots, s_{15}\} \quad (1)$$

where n means the cameras and n is 1 (front view) or 2 (side view).

3. Dynamic model

Motion usually takes in continuous frames. Therefore, it is important for each frame to connect with adjacent frames. For example, it would be one-foot jumping if a person jumps in a frame lifting one foot. However, it would be walking motion if a person leaves one foot on the ground and lifts the other foot. To resolve such confusions, we make a dynamic model which contains continuous frames of each movement. In this paper, we normalize a cycle of each motion to 10 frames because each motion usually takes 5~15 frames. If motion has no cycle as like stretching and balancing, we consider 10 frames as a cycle. So, the dynamic model of the motion c is

$$D_n^c = \{x_{n,1}, \ldots, x_{n,10}\} \quad (2)$$

where n means views (n =1 or 2).

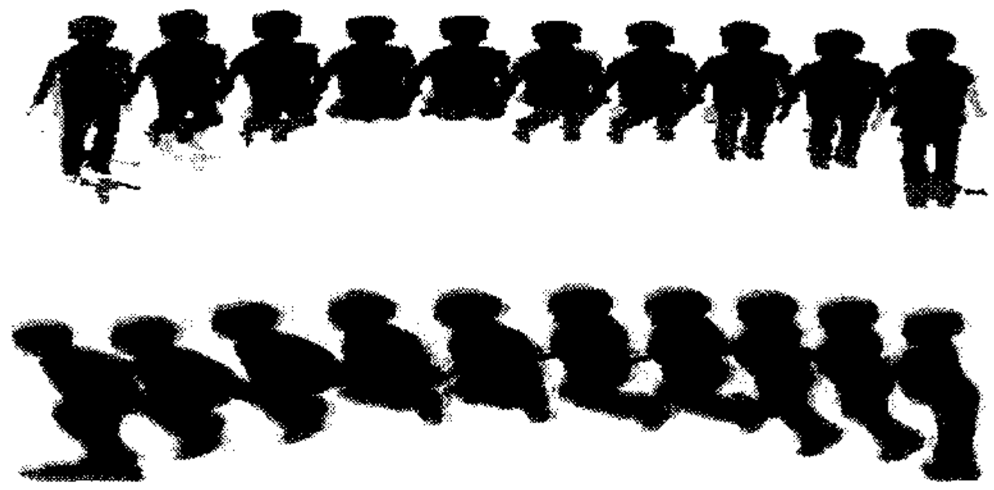


Fig. 5 Dynamic model of jumping (J) using 5 training video sets

[Fig. 4] shows the motion sequence of hopping at the front and one side view. Hopping motion is distinguished from jumping because it means to leap from one foot, and from walking because it means o stand on one foot continually. [Fig. 5] shows the dynamic model of jump movement.

IV. Silhouette-based pose estimation

One of the methods of human motion estimation extracts the features of motions from given data and reconstructs them. If it is hard to figure out the features of the motions, usually the density propagation models are used. Through the accumulated data from learning, one density propagation model is defined and it is constantly adjusted to the sample data. Eventually, the density propagation model satisfies the sample data. Many researchers tried to find out the status of model from the observation condition [5, 7, 10] or the state prior [3, 4, 9] through a Bayesian method. Brand and Hertzmann proposed the method in which they decided several parameters defining the formation of the motions, presumed the way to use the given motion data by a method using entropy minimization and form new motions [1]. Schodl *et. al* found out the features of the motions from the video data and figured out the probability of transfer [8]. Sminchisescu *et. al* estimated the motion of human by Bayesian Mixtures of Experts from the data of one camera [2].

The most obvious difficulties of the estimation lie in modeling the uncertainty of the silhouettes- or the probability density of the "distance" which is commonly used in the control community. The previous answer to the above question is to compute the whole probability density of the distance over time. We assume x_n^t and z_n^t are the target and observation at the n-th view at time t, respectively. Let $Z_n^t = \{z_n^0, \ldots, z_n^t\}$ be the history of observations up to time t at the n-th view. In this paper, x_n^t is the silhouette features of a human body, such as the one shown in Eq. (1).

At time t, for estimation of a silhouettes in a human motion c, the system computes the density function based on the extracted features as $P(c|x_{n,i}^t, Z_{n,i}^t)$ where $x_{n,i}^t$ and $Z_{n,i}^t$ are the i-th feature, i=1,⋯,25, of x_n^t and Z_n^t. Since the motion c can be represented as the corresponding dynamic model in Eq. (2), we estimate the density function of a silhouette by computing the distance between the silhouette and the dynamic model as

$$\sum_i \omega_{n,i} P\left(D_{n,i}^c | x_{n,i}^t, Z_{n,i}^t\right)$$

where $\omega_{n,i}$ is a weighting coefficient (typically uniform weights are used, i.e., i = 1/I) and $D_{n,i}^c$ is a dynamic model in Eq. (2).

V. Experimental results

1. Data sets

The proposed algorithm was implemented in Visual C++ and tested in Windows 2000 with a Pentium-IV 1.8 GHz CPU with 1GB of memory. The video frames used in this experiment were acquired with a Sony DCR-PC330 and Sony DCR-DVD805 at 15 frames per second (fps) with a resolution of 320×240. Two cameras were placed at the front and one side of each child. All children were five or six years of age and were in the kindergarten. Fifteen children participated in this experiment. They were asked to do seven movements three to five times. The system was trained on a sequence of 34 training video clip sets, alternating among seven movements [Table 3].

Table 3. Data sets where one set consists of two videos from two cameras.

Data sets	Movements						
	W	J	H	Be	S	Ba	T
Training video sets	5	5	5	5	5	5	4
Test clip sets	8	8	8	8	8	8	7

After silhouette extraction in incoming frames from two cameras, the system computed 25 features on each silhouette. To classify silhouette to motions, the system computes density estimation based on the extracted features. We make a dynamic model of each movement after calculating the average silhouette with training video clips. Each video clip usually consists of 5~30 frames, and we assume the result based on 10 frames.

2. Results

Table 4. Classification rate (%) on 550 test frame sets

Classification rate	Movements						
	W	J	H	Be	S	Ba	T
Frame-based	82	74	74	74	74	100	65
[17] with two cameras	93	89	74	64	94	100	56
Proposed method	89	93	94	80	84	100	74

[Table 4] shows the classification rates of the proposed method. For comparison, we compute frame-based classification by estimating motion frame-by-frame. While frame-based classification uses only information in each frame, the proposed method can use classification information in previous frames. For same test frames, we achieved 77.6% accuracy overall for frame-based classification and 87.8% accuracy overall for the proposed method, respectively we achieved 100% accuracy on balancing, 94% on jumping, 92% on hopping, 82% on walking, 80% on stretching, 76% on bending and 70% on turning. Especially, jumping(J) and hopping(H) can reduce confusion by using density estimation and dynamic models. For comparison, we modified Rosenhahn *et. al* [17] by using two cameras [17]. The modified Rosenhahn's algorithm achieved worse accuracies for Hopping, Bending and Turning, while it achieved better accuracies for Walking and Stretching.

Table 5. Confusion matrix on 550 test frame sets

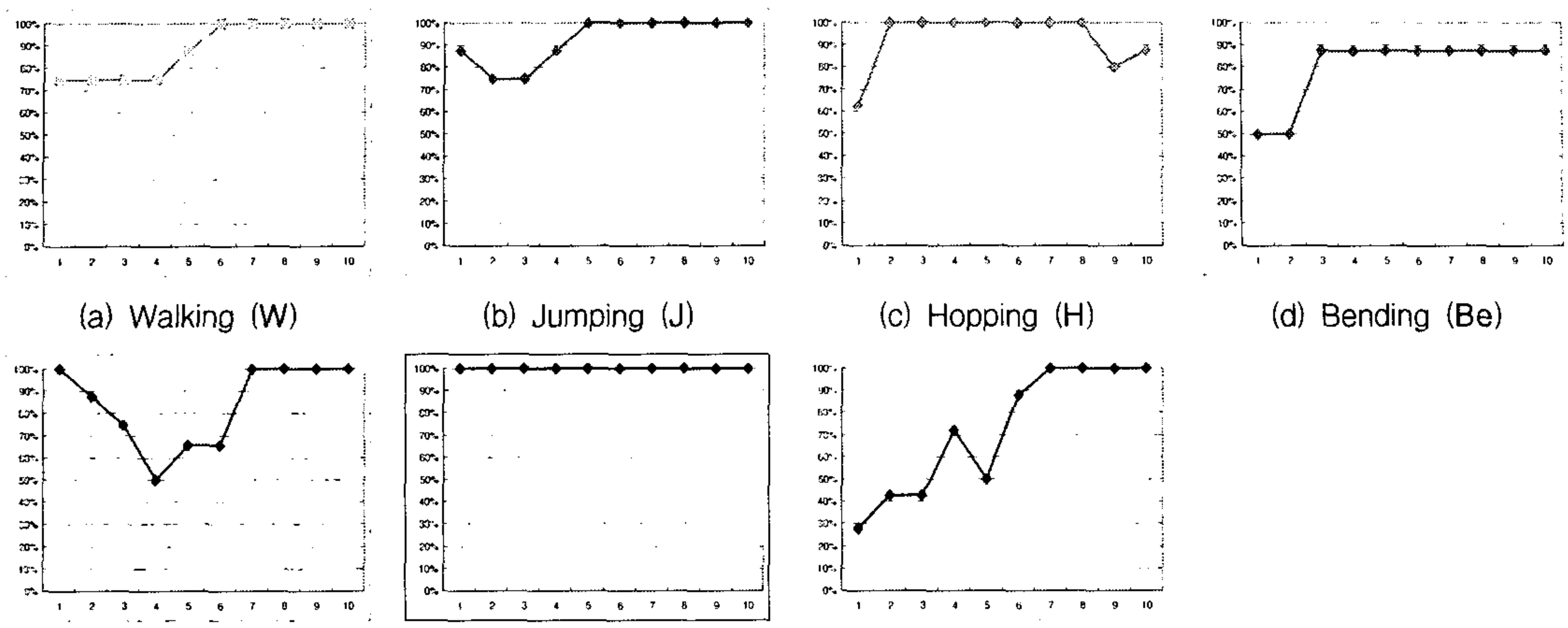
True movements	Estimated movements						
	W	J	H	Be	S	Ba	T
W. Walking	71	0	0	0	5	0	4
J. Jumping	0	74	6	0	0	0	0
H. Hopping	2	0	75	0	1	0	2
Be. Bending	0	0	0	64	0	0	16
S. Stretching	0	0	0	0	67	0	13
Ba. Balancing	0	0	0	0	0	80	0
T. Turning	0	13	1	0	2	0	54

[Table 5] shows the experiment results in a confusion matrix. The wrong results indicate that other movements were confused as turning movement. This is because the turning movement model includes some of bending or stretching movement. If the sequence model of turning is revised and supplemented, confusion with other movements can be reduced.

[Fig. 6] shows that as the system is preceded by sequences, its ability to correctly estimate the motions in test video clip sets increases. After a few beginning frames, the estimation rate stabilizes at 80% Bending[Fig. 6](d) and at 100% for Walking [Fig. 6](a), Jumping [Fig. 6](b), Turning [Fig. 6](g) and Balancing [Fig. 6](f). Stretching [Fig. 6](e) showed stable success rate after 7 frames. This is because the part of stretching movement includes movements similar to turning. Turning's estimated success rate increased, as frame increased, but the initial stage frame's success rate was so low that the lowest estimated success rate was exhibited.

VI. Conclusions and Discussions

This paper pursues to estimate seven fundamental movements presented in young children's movement education. In the existing offline young children's movement curriculum, classes were composed to teach only one movement and were carried out in a limited way. However, young children can learn various movements at a time through the system proposed in this paper. The movements used in the proposed system include the movements that have not been handled in the existing movement curriculum, and can help young children learn various movements. They can also be utilized as reality interface including virtual learning space.



(a) Walking (W) (b) Jumping (J) (c) Hopping (H) (d) Bending (Be)

(e) Stretching (S) (f) Balancing (Ba) (g) Turning (T)

Fig. 6 Estimation rate (%) for each movement sequence : X-axis means the number of frames and y=axis means classification rate(%).

Silhouette was extracted from each image acquired by two cameras deployed in a right angle, and the features used for perception and estimation were extracted from the extracted silhouette. Based on sequence models by movement using probability diffusion, 87.5% of success rate was acquired.

The method proposed in this paper estimated movements from the video frames acquired by video cameras without special tacking equipments, and thus a low priced movement estimation system was proposed. Because the method targeted young children, it showed differences from existing adult-targeted movement estimating methods. Based on the method, high efficiency was demonstrated by applying it to the method using probability diffusion method.

The system implemented in this research can be improved in the following methods and further research can be carried out in the future:

First, estimation success rate for turning has to be high. Turning movement showed the lowest success rate at 77% because turning is obscure compared to other movements and each young child demonstrates different movements. A method to precisely estimate turning movement in the system is required.

Second, the system proposed in this paper can be utilized in the early childhood educational settings. If the system is applied as interface for virtual learning space, or as game interface, young children can learn and experience movements under more diverse circumstances.

Third, from a methodology aspect, people can be designed as a partially composing model, not silhouette, so as to analyze movements. Human body parts are less sensitive to lighting changes, and they can be independently detected; therefore, the performance of component-based human body detection method is presumed to be better. Extracted features can also be extracted by transforming them into component-based features.

Though the proposed method considered the relationships with previous frames using probability diffusion, it is needed to apply to a method that estimates movements by each moving image, not in the unit of frame. In the future, this research should use the virtual learning system for practical movement education.

참 고 문 헌

[1] M. Brand and A. Hertzmann, "Style machines," in Proc. of SIGGRAPH, pp.183-192, 2000.

[2] C. Sminchisescu, A. Kanaujia, Z. Li, and D. Metaxas, "Discriminative density propagation for 3D human motion estimation," in Proc. of CVPR, Vol.I, pp.390-397, 2005.

[3] J. Deutscher, A. Blake, and I. Reid, "Articulated body motion capture by annealed particle filtering," in Proc. of CVPR, Vol.II, pp.126-133, 2000.

[4] G. Hager and P. Belhumeur, "Efficient region tracking with parametric models of geometry and illumination," IEEE transactions on PAMI, Vol.20, No.10, pp.1025-1039, 1999.

[5] N. Howe, M. Leventon, and W. Freeman, "Bayesian reconstruction of 3D human motion from single camera video," in Proc. of NIPS, Vol.12, pp.820-826, MIT Press, 1999.

[6] I. Pitas, Digital image processing algorithms and applications, Wiley-interscience, pp.352-356, 2000.

[7] S. Roth, L. Sigal, and M. J. Black, "Gibbs likelihoods for Bayesian tracking," in Proc. of CVPR, Vol.I, pp.886-893, 2004.

[8] A. Schodl, R. Szeliski, D. H. Salesin, and I. Essa, "Video textures," in Proc. of SIGGRAPH, pp.489-498, 2000.

[9] H. Sidenbladh, M.J. Black, and L. Sigal, "Implicit probabilistic models of human motion for synthesis and tracking," in Proc. of the ECCV, Vol.I, pp.784-800, 2000.

[10] H. Sidenbladh and M. J. Black, "Learning image statistics for Bayesian tracking," in Proc. of ICCV, Vol. II, pp.709-716, 2001.

[11] R. Laban, "Modern educational dance," Macdonald and Evans Ltd. London, 1963.

[12] 구성희, *유치원 교육 활동 지도 자료'에 나타난 동작 관련 활동 분석*, 이화여대 석사논문, 2002.

[13] 오연주, 이경실, 김현지, 박경애, 유아 동작 교육의 이론과 실제, 창지사, 2000.

[14] R. Kehl and L. J. Van Gool, "Real-time pointing gesture recognition for an immersive environment," in Proc. of AFGR, pp.577-582, 2004.

[15] A. Mittal, L. Zhao, and L. S. Davis, "Human body pose estimation using silhouette shape analysis," in Proc. of AVSS, pp.263-270, 2003.

[16] L. Ren, G. Shakhnarovich, J. K. Hodgins, H. Pfister, and P. A. Viola, "Learning silhouette features for control of human motion," ACM Graph, Vol.24, No.4, pp.1303-1331, 2005.

[17] B. Rosenhahn, U. G. Kersting, A. W. Smith, J. K. Gurney, T. Brox, and R. Klette, "A system for marker-less human motion estimation," in Proc. of DAGM, LNCS, 3663, pp.230-237, 2005.

[18] K. M. Lee and Y. M. Lee, "Tracking multi-person robust to illumination changes and occlusions," in Proc. of ICAT, pp.429-432, 2004.

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