

Kazakh Traditional Dance Gesture Recognition

A K Nussipbekov¹, E N Amirgaliyev¹ and Minsoo Hahn²

¹ Faculty of Mechanics and Mathematics, Al-Farabi Kazakh National University, Almaty, Kazakhstan

² Digital Media Lab, Korea Advanced Institute of Science and Technology, Daejeon, South Korea

E-mail: abai.nk@gmail.com

Abstract. Full body gesture recognition is an important and interdisciplinary research field which is widely used in many application spheres including dance gesture recognition. The rapid growth of technology in recent years brought a lot of contribution in this domain. However it is still challenging task. In this paper we implement Kazakh traditional dance gesture recognition. We use Microsoft Kinect camera to obtain human skeleton and depth information. Then we apply tree-structured Bayesian network and Expectation Maximization algorithm with K-means clustering to calculate conditional linear Gaussians for classifying poses. And finally we use Hidden Markov Model to detect dance gestures. Our main contribution is that we extend Kinect skeleton by adding headwear as a new skeleton joint which is calculated from depth image. This novelty allows us to significantly improve the accuracy of head gesture recognition of a dancer which in turn plays considerable role in whole body gesture recognition. Experimental results show the efficiency of the proposed method and that its performance is comparable to the state-of-the-art system performances.

1. Introduction

Gesture recognition is an important, interdisciplinary area which plays significant role in HCI (Human Computer Interaction) and it is used in a wide range of applications including robotics [1], medicine [2] computer games [3] education [4], sport [5] or dance as considered herein. Dance gesture recognition and classification is related to full body recognition task. Nowadays, the systems able to recognize and classify dance gestures, have a big impact on our day life. Recent researches like [6], [7] show that interactive gaming systems help to facilitate exercise and rehabilitation and even affect on academic performance. Interactive dance systems help to evaluate dancers performance [8] and can be used in online teaching [9].

There has been considerable progress on this topic, however the problem is still quite difficult and challenging. Correct pose estimation is one of the key components. One should take into account that pose estimation should be calculated in 3D space for better performance and robustness. Kazakh traditional dance recognition may differ from other types of dance recognition tasks because of the specificity of Kazakh traditional clothes (see figure 1). Some of the clothe parts can make it complicate to use some well known pose estimation techniques, while the other parts may conversely help to increase accuracy. Another point is that in Kazakh traditional dances the head movements are important, because there are a



lot of poses which may differ only in head orientation and that is why calculating correct head pose orientation is vital part for the accuracy of whole body recognition task.

Kazakh traditional dances date back to the old days of nomads and are historically and culturally valuable heritage. To the best of our knowledge, this problem has not been addressed anywhere yet. Figure 2 demonstrates the overview of our proposed system.

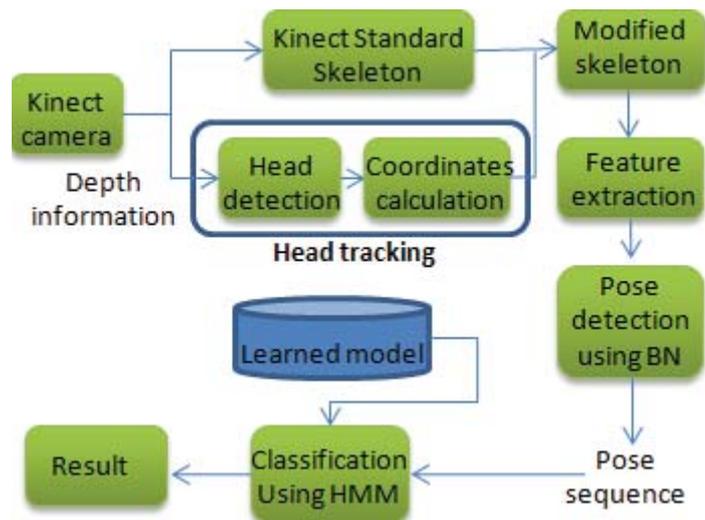


Figure 1. The specificities of Kazakh traditional women clothes are long and wide skirt and a high headwear called “Saukele”.

Figure 2. System Overview

In our work we extended the human skeleton, provided by Microsoft Kinect SDK, by applying headwear tracking. The modified skeleton (see figure 8a) is then used for pose recognition by learning tree-structured Bayesian network model using EM and k-means algorithm and finally gesture recognition is performed by applying Hidden Markov Model. As experiment results show, the proposed modified skeleton gives us more precise head movement information which, in turn, increases the recognition accuracy of the whole body for the Kazakh traditional dances.

2. Related Work

As dance gesture recognition is a special case of general gesture recognition task, many of the traditional approaches are used here. They have been addressed in many researches. Generally, these works can be divided according to the technology they use as well as the algorithm and techniques they apply for retrieving features and performing recognition.

There are many works which use different type of devices like electro-magnetic and optical sensors, accelerometers that are fixed on a human body or embedded in to the environment. For example [10] used body sensor network in their work, they applied hierarchical model in order to recognize actions on node (low) level and portable devices (high) level. Similarly, H. Junker *et al.* [11] used body-worn inertial sensors and used a kind of two stage approach, firstly using similarity search to select specific motion events and then classifying them by hidden Markov model. In contrast, [12] proposed to use smart clothes

based on conductive elastomer sensors which author say, is a new kind of strain sensors, compared to previous works, they were able to reconstruct shoulder, wrist, elbow and hands movements. There are some studies which are related directly to the dance gesture recognition problem using sensor approach. For instance, [13] created a real-time gesture driven interactive system with multimodal feedback for performing dance. In their study they operated with 41 markers attached to a dancer to obtain 3D coordinates of 10 body parts, however the latest Kinect SDK, which we use in our work, provides us with more body parts, in particular it includes hands and feet.

Another type of approaches are based on cameras. Camera based approaches, in turn, may also be divided into simple, stereo and depth cameras. Nam Vo *et al.* [14] have proposed to use skin color information taken from the web camera. They detect skin by recognizing face using boosted Haar wavelet classifier, determine skin with the help of thresholds, after that they use skin information to detect other parts and finally apply several recognition techniques. Additionally some other colorful objects may be used like colorful markers, gloves and etc. [15], [16]. An alternative approach is to use silhouettes as main feature. In [17], for example, they used silhouette energy image and variability models, and in [18], they proposed to adapt silhouette directionality-based feature vectors from silhouette contours.

Stereo cameras are yet another way not only to just recognize gestures but perform it in 3D space. Thus, [19] got high recognition results by using a novel approach based on multilinear analysis, they extracted low dimensional pose orientation coefficient vectors by performing tensor decomposition and projection.

Although all of the above mentioned works got promising results, they still have significant disadvantages. Sensors, for instance, are often cumbersome and movement-restraint, especially when there are too many wires. Another problem is that some of them are very expensive. Cameras are very sensitive to illumination and have certain complexities with occlusion, clutter and also often angle view dependent.

In terms of algorithms generally researchers can use Support Vector Machine (SVM) [17], [19], Neural Networks [20], K-means clustering [18], decision trees [15], Hidden Markov Model [1], [21], [22] and many other approaches are used today. Choosing appropriate algorithm depends on the purpose of work.

In our own method we use a Kinect camera which was launched in 2010 by Microsoft (see figure 3). It has been used in a wide range of researches like [4], [9]. The advantage of this camera over other traditional ones is that beside its RGB camera and multi-array microphone, it includes an infrared laser projector combined with a monochrome sensor, that allows it to capture 3D scenes in any available lighting conditions. Latest Kinect SDK provides developers with 640x480p depth image and skeleton consisting of 20 joints. Kinect has many benefits unlike previously explained methods: people do not need to wear special sensors which make it natural to use, it does not suffer from the shortage of illumination as regular cameras do, it gives more precise 3D coordinates and at the same time it's angle view independent compare to monocular cameras and some other advantages that make it better to use in our work. In our project we used Bayesian network for skeleton to robustly detect poses, and by using Kinect we didn't have to use additional skeletonization procedures to get skeleton information as it was done by K. Srijevanthan *et al.* [23], [22] and then used in their another study for their framework. In terms of classification algorithms, we used Expectation Maximization and standard k-means algorithm to detect poses and Hidden Markov Model to determine the sequential nature of movements.

3. Feature extraction and preprocessing

3.1 Skeleton features extraction

As it was mentioned above, Kinect provides us with skeleton consisting of 20 joints each having its 3D coordinates (X, Y, Z). Using human skeleton instead of other approaches explained before gives us several advantages. First of all, we do not rely on dancer's visual appearance like color of clothes. Moreover, despite the fact that people skeleton can be different in size, such as they may have different bone lengths, by using joint angle values as a feature set instead of joint coordinates, we make our system person independent. In our work we adopted similar features proposed in [24]. We use inclination and azimuth angle values (see figure 4) of particular joint vectors. These joints are: Right Hand (RH), Left Hand (LH), Right Elbow (RE), Left Elbow (LE) and Head.

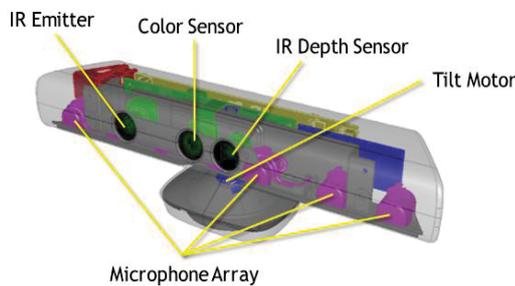


Figure 3. Kinect camera

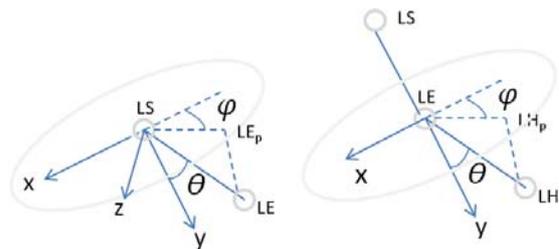


Figure 4. Spherical coordinate system for first (left) and second-degree (right) joints (LH-left hand, LS-left shoulder, LE-left elbow, LE_p and LH_p – their projections, θ -inclination angle, φ -azimuth angle)

Joints were divided into first-degree, like head and elbows which are calculated relative to torso, and second-degree joints, like hands that are calculated relative to its parent joint (see figure 4). Because of specificity of Kazakh traditional clothes (see figure 1), legs can't be tracked directly from Kinect skeleton. Inferred joints that supposed to help in such situations often make unrealistic motion. It could be possible to use depth silhouette or color information for this problem but it will degrade time performance of the overall system. On the other hand, we observe that leg movements are not so important in recognition of Kazakh traditional dances.

3.2 Skeleton modification

Head movements are important in Kazakh traditional dances and their precise angle calculation is essential. We observe that standard Kinect skeleton can not give us a favorable head tracking accuracy, so we decided to use our own method that is based on dancer's headwear tracking.

In our proposed method, firstly, we isolate a human performing dance from the background. We do it by performing background subtraction based on auto thresholding principle proposed by [25] after obtaining histogram of depth image (see figure 5). Next, we calculate a region of interest (ROI). It is an area which is just over the head (see figure 6). The location of ROI is calculated by using Kinect skeleton head location information and its size calculated depending on how far a performer stands from the camera. After, we search for headwear in that region by observing "blobs", there are a lot of ready solutions for such kind of problems and in our project we used EmguCV library for that purpose. Then we calculate the center of mass of our object by calculating image moments. We find X and Y coordinate on the image, and after, we

calculate a depth value at that point. Finally we have to transform these coordinates to the real world ones. We map them to Kinect skeleton and thus get X, Y, Z world coordinates of our headwear.

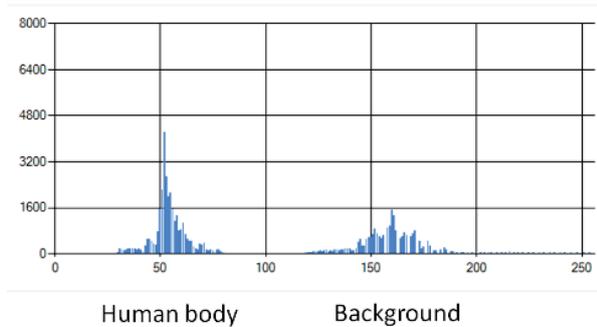


Figure 5. Depth histogram.

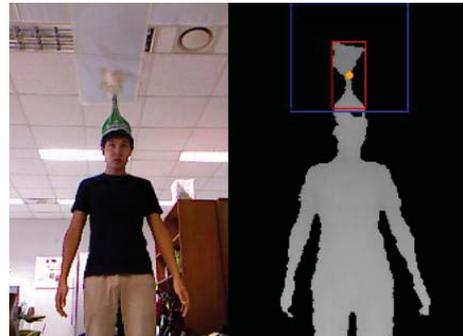


Figure 6. ROI and headwear calculation from depth image.

In order to test our proposed method we fixed laser on the top of the headwear and a linear grid, marked with distance values, to the ceiling of a room and then observed the displacement (w) of the laser point on that grid (see figure 7). Knowing the distance between a person's headwear and ceiling (h), we calculated real head inclination angle values, which is $\arctan(\theta)$, and compared them with our proposed method and Kinect skeleton's head inclination values (see figure 9). Experiment results demonstrate that our proposed new calculated skeleton "bone" (see figure 8a) gives us more precise and accurate head inclination values (see figure 9a, 9c) compare to standard skeleton's head (see figure 9b, 9d). We made this experiment in XY and YZ plane and we noticed that this is especially noticeable for small head inclinations and inclinations in YZ plane.

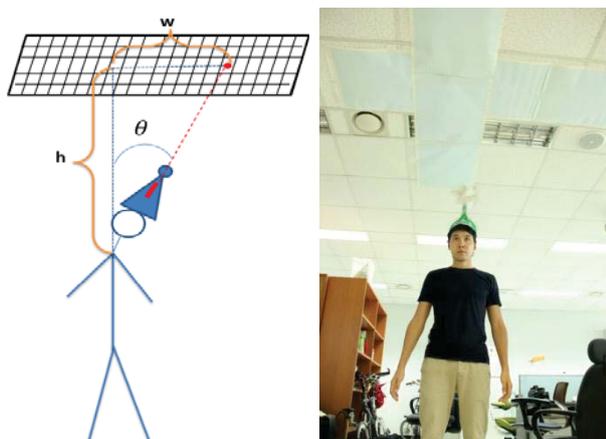


Figure 7. Measurement of real inclination angle values of head.

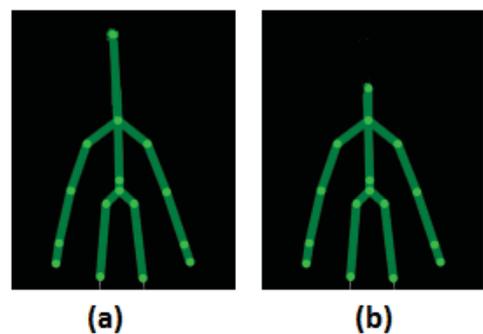


Figure 8. a) extended skeleton. b) standard skeleton

Another thing that we found is that our proposed method produces more clear and expressed graph (see figure 10 a) of head movements from which we can easily extract features we need compared to standard skeleton. Standard skeleton's head, in turn, experiences jitters while moving which affects on the diagram (see figure 10 b) of periodical head movements.

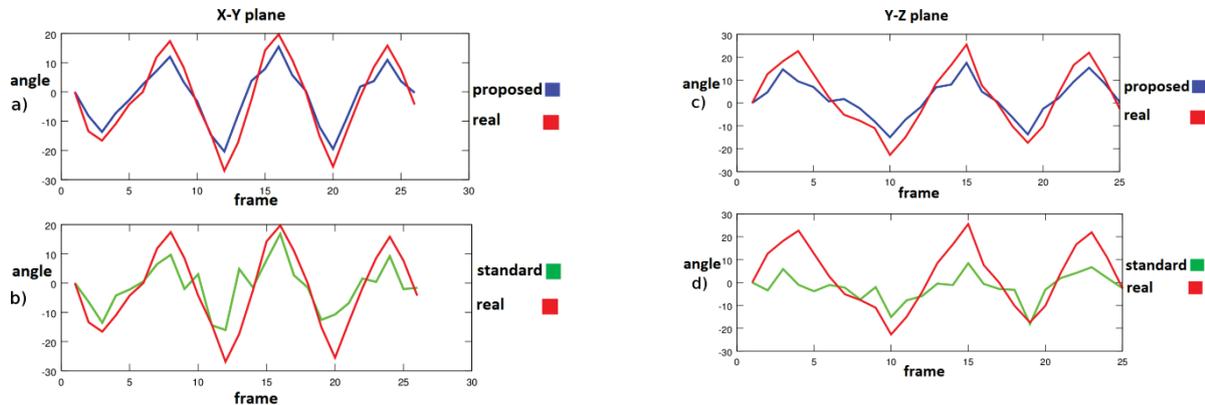


Figure 9. Comparison of head inclination values using proposed head tracking method (a), (c) and values taken from Kinect skeleton's head (b), (d) with real values

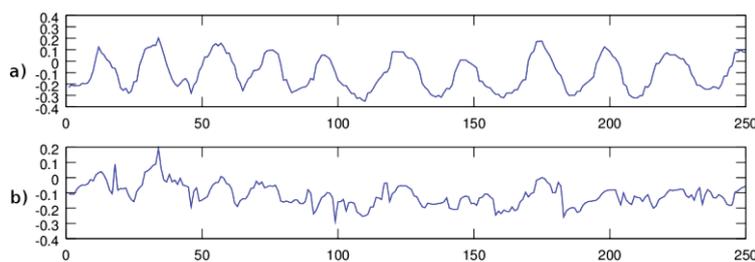


Figure 10. Proposed method (a) gives more clear and expressed diagram compare to Kinect skeleton's head (b) gives.

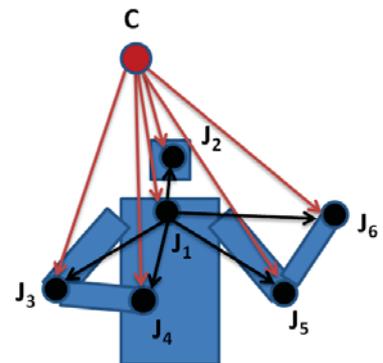


Figure 11. Skeleton. Joint (J) and class (C) dependencies.

4. Recognition

4.1 Pose recognition

Tree structured models and Bayesian network has been widely used in human pose estimation [26], [27]. The recently opened Stanford PGM online course [30] also adopted it in their class. We used an improved version of their proposed model for our own purposes.

The good thing about them is that it allows us not only to represent a pose but to take into consideration the kinematic constraints of human body structure. In other words it takes into account different dependencies among body parts which makes the pose estimation more realistic and efficient.

The structure is shown in figure 11. Each node except torso (J_1) has its own physical parent node and class parent node whom it belongs to. Class node represents a posture class. A torso, being a root node, has only one parent node which is a class node. We parameterize CPD values of each node by using Gaussian and Conditional Linear Gaussian (CLG) distribution.

A torso is parameterized by following simple Gaussian distribution:

$$\theta | C = k \approx N(\mu_k^\theta, \sigma_k^{\theta 2}), \quad (1)$$

$$\varphi | C = k \approx N(\mu_k^\varphi, \sigma_k^{\varphi 2}), \quad (2)$$

where k are indexes of pose classes. Other body parts have two parents, thus they will be parameterized by following linear Gaussian (CLG):

$$\theta_i | J_{p(i)}, C = k \approx N(\beta_{ik}^{(1)} + \beta_{ik}^{(2)}\theta_{p(i)} + \beta_{ik}^{(3)}\varphi_{p(i)}, \sigma_{ik}^{\theta 2}), \quad (3)$$

$$\varphi_i | J_{p(i)}, C = k \approx N(\beta_{ik}^{(4)} + \beta_{ik}^{(5)}\theta_{p(i)} + \beta_{ik}^{(6)}\varphi_{p(i)}, \sigma_{ik}^{\varphi 2}), \quad (4)$$

where $i = 1, 2, \dots, 5$ are body part indexes, k is the pose class number, $p(i)$ is the parent of i 'th node.

Each class of pose is related to its own set of conditional linear Gaussian parameters. And we learn these parameters performing Expectation Maximization (EM) algorithm by iterating between calculating probabilities of pose classes $P(C = k | J_1, \dots, J_6)$ which, in turn, calculated from the joint probability of pose and class, and estimating CLG values using these probability values.

For better performance we added standard k -means clustering algorithm before running EM algorithm which classifies pose classes in order to use them as initial class probability values in EM algorithm.

In our study each posture class is represented as a unique symbol which is used in our following part.

4.2 Gesture recognition

Now, having obtained the set of poses, we would like to determine the gesture to which this sequence belongs to. We use discrete Hidden Markov Model (HMM) in this problem because they handle the sequential nature of the gestures consisting of these poses.

HMM was explained in details in a Rabiner's tutorial [28]. It is characterized by N hidden states $S = \{S_1, S_2, \dots, S_N\}$ and M observation symbols (alphabet) $V = \{v_1, v_2, \dots, v_M\}$. The transition probability between states is in $N \times N$ matrix $A = \{a_{ij}\}$ where $a_{ij} = P[q_{t+1} = S_j | q_t = S_i]$, q_t is a state at time t . The observation probability matrix $B = \{b_j(k)\}$, where $b_j(k) = P[v_k | q_t = S_j]$, where $1 \leq k \leq M$ and $1 \leq j \leq N$. And the initial state distribution probability $\pi_i = P[q_1 = S_i]$. HMM is used for different kind of problems that can be divided into two types: inference and learning.

In our work we use HMM to firstly learn models of different dance gestures and then use them for calculating the probability of some specified sequence of poses (observed sequence). Learning a model is the problem of adjusting the model parameters $\lambda = (A, B, \pi)$ to maximize the probability of output symbols given the model. It is solved by using Baum-Welch algorithm.

Every taken gesture from camera is, as it was mentioned above, represented as a sequence of symbols which we recognize by calculating $P(O|\lambda)$, the probability of observation sequence $O = O_1O_2...O_T$, given the model λ and selecting the class which gives the highest probability for a given observation

$$\arg \max\{P(O|M_1), P(O|M_2), \dots, P(O|M_n)\}, \tag{5}$$

where M_i is HMM model for i 'th gesture and n is number of gestures.

5. Experiment results

We analyzed many Kazakh traditional dances and noticed that many of them share same or almost same gestures. Therefore we decided to classify gestures rather than whole dances. There are no specific names for these gestures so we named them according to their main poses [31]. In our experiment we used 12 dancers each performing 10 dance gestures from different dance types 5 - 8 times. The dataset was manually labeled. In total we collected about 800 dance gestures, 70% of which was used for training and the remaining 30% for testing. We evaluated our and the following table 1 demonstrates results.

Table 1. Gesture recognition accuracy results.
Accuracy (a) - initial recognition result, accuracy (b) - after adding headwear tracking.

Dance gesture	Accuracy (a)	Accuracy (b)
Salem	84.0%	84.2%
Qus qanat	97.0%	98.7%
Qos muyiz	92.1%	97.3%
Saukele	85.0%	92.0%
Sanyr muyiz	83.3%	87.6%
Belbeu	90.8%	90.0%
Kamshy	86.0%	89.1%
Qol zhaiyu	86.7%	89.4%
Shashyn oru	79.4%	85.8%
Aq qu	88.0%	94.1%
		90.82%

$$Accuracy = (N_c \times N_T^{-1}) \times 100, \tag{6}$$

where, N_c - number of correctly classified gestures, N_T - total number of gestures.

It can be seen from the table that the lowest final performances among our selected gestures is 84%. This is because of noise persisting in Kinect depth image which affects on skeleton accuracy for low expressed movements e.g. Qol Zhaiyu and Shashyn Oru gestures, another reason is that joints can overlap each other which affects on azimuth angle calculation accuracy e.g. Salem gesture.

However by using our new head tracking approach we got higher accuracy (see table1 Accuracy (b)) for such gestures like Aq Qu (94.1% compare to 88%), Saukele (92% compare to 85%), this is because head movements are one of the key components in these gestures. Other gestures, where head movements are not so expressed, remained almost the same. Kazakh traditional dances are different from many other dances. And as it was mentioned above, to the best of our knowledge, this problem has not been addressed anywhere yet so we cannot compare it with other works. But generally 90.82% is a very good accuracy on the dance recognition task. For example [29] has got 92% on average for the recognition of Bali traditional dances.

6. Conclusion

“Kazakh traditional dance gesture recognition” is interesting and challenging task. We used Microsoft Kinect camera in our work in order our system to be easy and natural to use. We adopted some well known statistical models like Bayesian network, hidden Markov models and used appropriate algorithms like EM algorithm, k-means clustering, Gaussian distribution to parameterize and learn these models. Our main contribution however was improvement of head gesture recognition by our own proposed head tracking method. Finally we got high recognition results which are demonstrated in last section. The proposed work carries a cultural significance for Kazakh traditions. It may be used for dance evaluation systems as well as in computer games.

References:

- [1] H. Yang, A. Park, S. Lee, and S. Member, “Gesture Spotting and Recognition for Human – Robot Interaction,” vol. 23, no. 2, pp. 256–270, 2007.
- [2] K. Englmeier, C. Krapichler, M. Haubner, M. Seemand, and M. Reiser, “Virtual reality and multimedia human-computer interaction in medicine.”
- [3] M. Labs and M. Corporation, “USING HUMAN BODY GESTURES AS INPUTS FOR GAMING VIA DEPTH ANALYSIS,” pp. 993–996, 2008.
- [4] V. Thakkar, A. Shah, M. Thakkar, A. Joshi, and N. Mendjoge, “Learning Math Using Gesture,” *International Conference on Education and e-Learning Innovations*, pp. 1–3, Jul. 2012.
- [5] K. Takano and K. F. Li, “Classifying Sports Gesture Using Event-Based Matching in a Multimedia E-learning System,” *2012 26th International Conference on Advanced Information Networking and Applications Workshops*, pp. 833–838, Mar. 2012.
- [6] Z. Gao, P. Hannan, P. Xiang, D. F. Stodden, and V. E. Valdez, “Video game-based exercise, Latino children’s physical health, and academic achievement.,” *American journal of preventive medicine*, vol. 44, no. 3 Suppl 3, pp. S240–6, Mar. 2013.
- [7] M. J. D. Taylor, D. McCormick, T. Shawis, R. Impson, and M. Griffin, “Activity-promoting gaming systems in exercise and rehabilitation,” *The Journal of Rehabilitation Research and Development*, vol. 48, no. 10, p. 1171, 2011.

- [8] J. James, T. Ingalls, G. Qian, L. Olsen, D. Whiteley, S. Wong, and T. Rikakis, "Movement-based interactive dance performance," *Proceedings of the 14th annual ACM international conference on Multimedia - MULTIMEDIA '06*, p. 470, 2006.
- [9] S. Essid, D. Alexiadis, R. Tournemene, M. Gowing, P. Kelly, D. Monaghan, P. Daras, A. Dreameau, and N. E. O'Connor, "An advanced virtual dance performance evaluator," *2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 2269–2272, Mar. 2012.
- [10] L. Wang, T. Gu, X. Tao, and J. Lu, "A hierarchical approach to real-time activity recognition in body sensor networks," *Pervasive and Mobile Computing*, vol. 8, no. 1, pp. 115–130, Feb. 2012.
- [11] H. Junker, O. Amft, P. Lukowicz, and G. Tröster, "Gesture spotting with body-worn inertial sensors to detect user activities," *Pattern Recognition*, vol. 41, no. 6, pp. 2010–2024, Jun. 2008.
- [12] D. De Rossi, R. Bartalesi, F. Lorussi, a. Tognetti, and G. Zupone, "Body Gesture and Posture Classification by Smart Clothes," *The First IEEE/RAS-EMBS International Conference on Biomedical Robotics and Biomechatronics, 2006. BioRob 2006.*, pp. 1189–1193.
- [13] T. Ingalls, L. Olson, J. James, and T. Rikakis, "A gesture-driven multimodal interactive dance system," *2004 IEEE International Conference on Multimedia and Expo (ICME) (IEEE Cat. No.04TH8763)*, pp. 1579–1582, 2004.
- [14] N. Vo, Q. Tran, T. B. Dinh, T. B. Dinh, and Q. M. Nguyen, "An Efficient Human-Computer Interaction Framework Using Skin Color Tracking and Gesture Recognition," *2010 IEEE RIVF International Conference on Computing & Communication Technologies, Research, Innovation, and Vision for the Future (RIVF)*, pp. 1–6, Nov. 2010.
- [15] Y. Iwai, K. Watanabe, Y. Yagi, and M. Yachida, "Using Colored Gloves," pp. 662–666, 1996.
- [16] H. Ukida, S. Kaji, Y. Tanimoto, and H. Yamamoto, "Human Motion Capture System Using Color Markers and Silhouette," no. April, pp. 151–156, 2006.
- [17] M. Ahmad and S.-W. Lee, "Recognizing human actions based on silhouette energy image and global motion description," *2008 8th IEEE International Conference on Automatic Face & Gesture Recognition*, pp. 1–6, Sep. 2008.
- [18] M. Singh, S. Member, A. Basu, and S. Member, "Human Activity Recognition Based on Silhouette Directionality," vol. 18, no. 9, pp. 1280–1292, 2008.
- [19] B. Peng and G. Qian, "Binocular dance pose recognition and body orientation estimation via multilinear analysis," *2008 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*, pp. 1–8, Jun. 2008.

- [20] N. Kim, Y. An, and B. Cha, "Gesture Recognition Based on Neural Networks for Dance Game Contents," *2009 International Conference on New Trends in Information and Service Science*, pp. 1134–1139, Jun. 2009.
- [21] L. Xia, C. Chen, and J. K. Aggarwal, "View Invariant Human Action Recognition Using Histograms of 3D Joints The University of Texas at Austin," pp. 20–27, 2012.
- [22] C. N. Joseph, S. Kokulakumaran, K. Srijevanthan, a. Thusyanthan, C. Gunasekara, and C. D. Gamage, "A framework for whole-body gesture recognition from video feeds," *2010 5th International Conference on Industrial and Information Systems*, pp. 430–435, Jul. 2010.
- [23] K. Srijevanthan, a Thusyanthan, C. N. Joseph, S. Kokulakumaran, C. Gunasekara, and C. Gamage, "Skeletonization in a real-time gesture recognition system," *2010 Fifth International Conference on Information and Automation for Sustainability*, pp. 213–218, Dec. 2010.
- [24] M. Raptis, D. Kirovski, and H. Hoppe, "Real-time classification of dance gestures from skeleton animation," *Proceedings of the 2011 ACM SIGGRAPH/Eurographics Symposium on Computer Animation - SCA '11*, p. 147, 2011.
- [25] P. T. Using and I. S. Method, "Picture Thresholding Using," no. 8, pp. 630–632, 1978.
- [26] L. Zhang, J. Chen, Z. Zeng, and Q. Ji, "2D and 3D upper body tracking with one framework," *2008 19th International Conference on Pattern Recognition*, pp. 1–4, Dec. 2008.
- [27] D. P. Huttenlocher, "Beyond trees: common-factor models for 2D human pose recovery," *Tenth IEEE International Conference on Computer Vision (ICCV'05) Volume 1*, pp. 470–477 Vol. 1, 2005.
- [28] L. R. Rabiner, "A tutorial on hidden Markov models and selected applications in speech recognition," *Proceedings of the IEEE*, vol. 77, no. 2, pp. 257–286, 1989.
- [29] Y. Heryadi, M. I. Fanany, A. M. Arymurthy, F. I. Komputer, and U. Indonesia, "A Syntactical Modeling and Classification for Performance Evaluation of Bali Traditional Dance," pp. 978–979, 2012.
- [30] Probabilistic Graphical Models by Daphne Koller, available at <https://www.coursera.org/course/pgm>, December 8, 2013
- [31] Pazilova M. K., Shiskkova N.V., "Kazakh Dances", Omsk Regional College of Culture and Arts, 2010.