Squat Movement Recognition Using Hidden Markov Models

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***Abstract*— This paper proposes a novel squat movement recognition system using hidden Markov models (HMMs), whose data is captured by Perception Neuron (PN) [1]. Here, the PN generates entire skeleton data of human body in each frame and uses them to form a data stream in real-time. In our experiments, we collect the data streams of 6 squats including a standard one with 5 non-standard ones. Based on the HMMs learned by these data streams, our proposed recognition system can correctly distinguish the patterns of the non-standard squats from the standard one. Our experimental results show that the recognition accuracies of the standard squat and 5 non-standard ones reach high level, respectively.**

Keywords—Hidden Markov Models; Squat Movement Recognition

I. Introduction

Human movement recognition can be considered as the most widely known research subject in computer vision, compared with many other challenging issues. It has been recently used in various applications, especially in the fields of healthcare and physical therapy [2], [3]. Since the improved movement recognition can learn more correct human movement patterns to reach the desired specification, it is possible to make more cost-effective and better, home-based rehabilitation and health-care systems, which will be globally valuable in the future.

Here, the squat, discussed in this paper, is one of the most common exercises for health improvement and muscle strengthening [4], because it involves nearly every muscle in the body. Its popularity reflects its practicality. Therefore, it can be regarded as a fundamental human movement pattern in human movement recognition. However, most people make five common mistakes that reduce the effects of squat [5], [6]. The first mistake is considered as lowering the body so inadequately that the thighs are not parallel to the ground. The second, third, fourth, and fifth ones are collapsing knees inward, lifting heels, letting knees past the toes, and rounding lower back, respectively. People that make these mistakes usually experience difficulties in controlling their body and muscle. On the other hand, the standard squat is standing up straight, keeping feet hip-width apart, and raising hands to body sides. Meanwhile, it is necessary to bend the knees until the thighs are parallel to the ground, and keep heels on the ground and straighten back (spine). Moreover, in order to prevent kneecaps being turned on the outsides of the feet, the knees need to be moved backward from the toes [7].

Moreover, for methodology, hidden Markov models (HMMs) has been regarded as an effective machine learning method for recognizing the human movement [8] in recent years. Paper [9] proposed a human movement recognition system based on a multivariate and continuous HMM classifier. It gave an evaluation on motion capture dataset to determine which HMM obtained high recognition rate.

The purpose of this paper is to recognize 5 common non-standard squats shown in Fig. 1 by the trained HMMs. This work not only helps users to correct their squat but also provides us an opportunity to evaluate the performance of the HMMs. As illustrated in Fig. 2, the proposed recognition system originally tracks the movement of a segmented human body by Perception Neuron (PN) [1], which is a sensor suit for human movement capture.

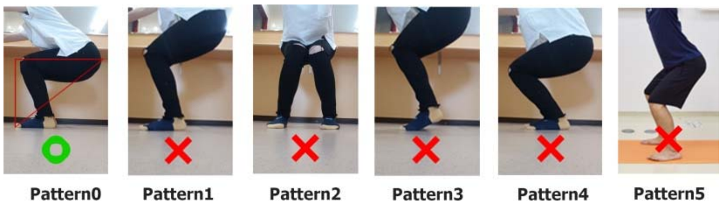

Fig. 1. Patterns of the common standard and non-standard squats.

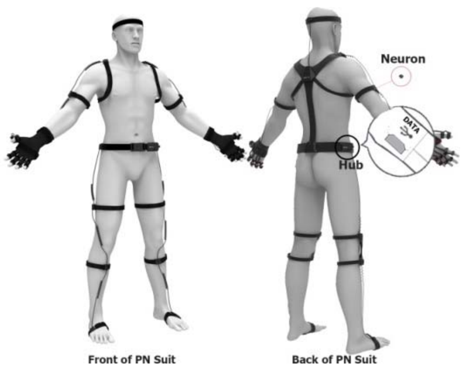

Fig. 2. Perception Neuron motion capture suit.

II. Proposed Method

An overview of this system is shown in Fig. 3. First, the training data streams captured by the PN are preprocessed for easy computation. Then they are learned by the HMMs. The test data streams are also preprocessed and substituted into the trained HMMs for the squatting recognition. Here, the PN for one person consists of 8 inertial measurement unit (IMU) neurons, which are respectively equipped with the human parts in the following order (1. hips, 2. right-up leg, 3. right leg, 4. right foot, 5. left-up leg, 6. left leg, 7. left foot, 8. chest). Each neuron provides 6 motion sensing, i.e., accelerometer for X, Y, and Z axes, and gyrometer for

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measuring the roll, pitch, and yaw. If a one-time squat costs about 4 seconds and the capturing speed of the PN is 69 frames/sec, the size of the squat data stream approximates 6×8×69×4≈48×400. The evaluation method is performed on the dataset presented in Table 1 and visualized in Fig. 4, where the data represents a standard squat (Pattern 0).

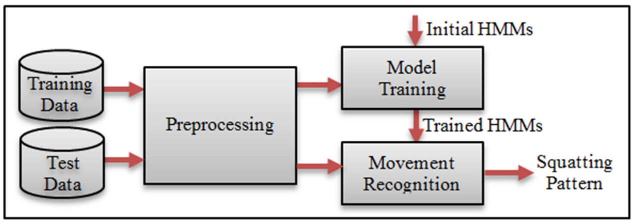

Fig. 3. Overview of the recognition system.

Table 1. The data sample of standard squat provided by squatting trainer (Pattern 0).

Name of Bone	pos_x	pos_y	pos_z	gyro_x	gyro_y	gyro_z
Hips	1.038986	2.525553	2.917285	-0.25785	-2.50748	-3.55527
RUL	1.091409	1.911178	2.312678	4.564859	-4.70748	-5.05467
RL	0.707077	1.467741	2.1707	0.441808	0.015072	-1.71661
RF	0.267207	0.802372	2.103937	0.865103	0.573412	-0.16992
LUL	0.225846	2.472516	1.893791	-1.01002	-3.82228	-2.11021
LL	-0.49086	2.240195	1.940907	-3.43902	-3.36469	4.422192
LF	-1.12301	1.720875	2.105249	-4.04097	-2.48284	-3.48375
Spine	0.411367	0.344294	-1.63534	-2.69295	-3.57324	0

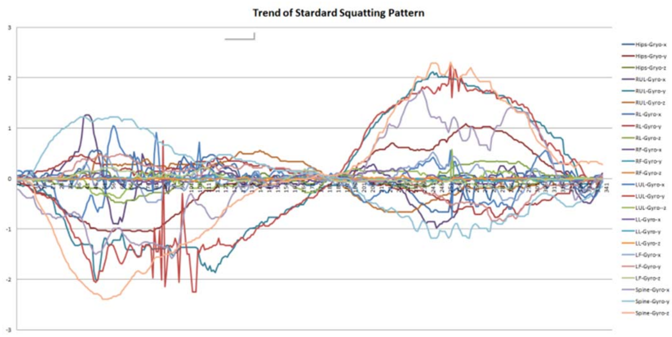

Fig. 4. The time series data sample of standard squat provided by squatting trainer (Pattern 0).

A. Preprocessing

For further recognition, it is convenient to normalize the original data streams from PN. It means that after feature selection, each feature value needs to be transformed to the Z-score:

$$Z = \frac{X-\mu}{\sigma} \quad , \tag{1}$$

where X is the values of single feature, μ is the mean value of X, and σ is the standard deviation of X.

B. Model Traning and Movement Recognition

The HMMs in our system are denoted as $\lambda = \{n, A, B, \pi\}$. Here, n is an integer representing the total number of states in the system; A is a matrix of transition probabilities; B is either a matrix of observation probabilities (in the discrete case) or a vector of probability distributions (in the general case); $\pi = \{\pi_1, \pi_2, \dots, \pi_q\}$ is a vector of initial state probabilities determining the probability in each of the possible starting states in the model. An overview of this process is shown in Fig. 3. We utilize Baum-Welch learning method to estimate the HMM parameters [10]. It is also possible to create an HMM-based classifier that decides which of n-classes a given data belongs to. In our case, the classifier is composed of n HMMs (the number is same as that of action classes). The parameters of each HMM are estimated on exemplars of data from different classes. Then when unknown data is being examined, it can be classified to one class based on which HMM corresponding to this class has the largest probability to produce the sequence.

III. Experimental Results

In experiments, one squatting trainer did every squat 50 repetitions as the training data. Additionally, 10 participants (6 males and 4 females) freely did squat 3 sets of 10 repetitions to build the test data. Here, the test data was the raw motion-capture data made by Axis Neuron program. We compared it with the standard or non-standard patterns learned from the training data, and decided which of the patterns it belongs to by ourselves. The decision results were considered as the ground truth of the test data in our experiment.

Our recognition system was evaluated as follows. First, the HMM classifiers in our system were composed of 6 HMMs (the number is same as that of action classes) with 10 states (q = *10*). Each of them was trained to recognize one squatting pattern through the training data provided by squatting trainer. Then after training, 6 postures of human skeletons were generated by PN to show the corresponding squatting patterns, which are presented in Fig. 5.

In testing, the trained HMM classifiers distinguished the training data into the 6 squatting patterns according to the highest probability to produce the sequence in HMM. Table 2 presents the average recognition accuracies of all squatting patterns by HMMs. Those indicate that the No.4 squatting pattern is easiest to be recognized with 76% accuracy. In addition, the recognition accuracies of standard squatting and non-standard squatting patterns reach 92% and 75.85%, respectively.

Table 2. The recognition accuracies of squatting patterns for training data.

	Pattern					
	0	*1*	*2*	*3*	*4*	*5*
Accuracy (%)	92	62	81.63	82	77.6	76

In order to investigate the generalization ability of our recognition system, we also used it to recognize the test data of 10 participants. After this, we obtained the corresponding recognition quantities of the standard and 5 non-standard squats of every participant in our dataset, which are showed in Table 3. As can be seen from this table, not every person could practice well following the standard squat. That was because most of those participants had never done squats before. Moreover, around the end of test, the participants were getting tired, thus their squats became more abnormal than at the beginning. On the other hand, it was obvious that there existed two participants who had experience doing squats (M1 and M3).

Table 3. The recognition quantities of squats for every participant in dataset.

Dataset	Test set no.	Pattern					
		0	*1*	*2*	*3*	*4*	*5*
F1	1	5	4	2	15	2	2
M1	2	12	2	10	1	2	3
M2	3	2	4	5	2	6	11
M3	4	14	0	0	8	0	8
F2	5	2	1	10	2	13	2
F3	6	1	4	13	5	4	3
F4	7	0	2	8	7	10	3
M4	8	0	0	4	12	3	11
M5	9	1	4	4	9	0	12
M6	10	2	6	1	8	2	11

The evaluation results including recognition sensitivities, specificities, and accuracies of the 6 patterns are presented in Table 4. Based on these results, we determined that the system was able to identify the standard squat (Patten 0) with a higher accuracy than every non-standard one (Pattern 1-5). However, we also found that some kinds of squats are too confused to be clearly distinguished from others. For example, lowering the body inadequately and collapsing knees not non-parallelly while lifting heels always occurred in Pattern 2 and 4, not only in Pattern 1. For this reason, the data of the Pattern 1 could be recognized incorrectly with a lower sensitivity.

Table 4. The sensitivities, specificities, and accuracies of squatting patterns for test data.

	Pattern					
	0	*1*	*2*	*3*	*4*	*5*
Sensitivity (%)	52.20	8.60	69.23	60.41	44.12	42
Specificity (%)	98.28	92.10	88.71	81.75	87.95	80.4
Accuracy (%)	88	79.30	85.33	78.33	53.67	74

Fig. 6 shows the interface of our recognition system, which was built in Unity3D with C# and depending on the HMM libraries of Accord Framework [11].

IV. CONCLUSION

This paper presented a novel squat movement recognition system using HMMs. It could recognize the 5 non-standard squats from the standard one. The proposed method and experiment results presented in this paper are useful both from realistic and theoretical points of view. Practically, our method can be directly implemented into squat training applications in multimedia computer to create an intelligent system. In addition, it can also help users to correct their squats and stimulate them to further efforts.

However, it is very difficult to apply the proposed method to evaluate the quality (similarity to "ideal pattern") of the squat exercise when we are using PN at the current stage. Because of the magnetic interference issue of the sensors, the data streams captured by the PN were unstable. We will improve it in our future works.

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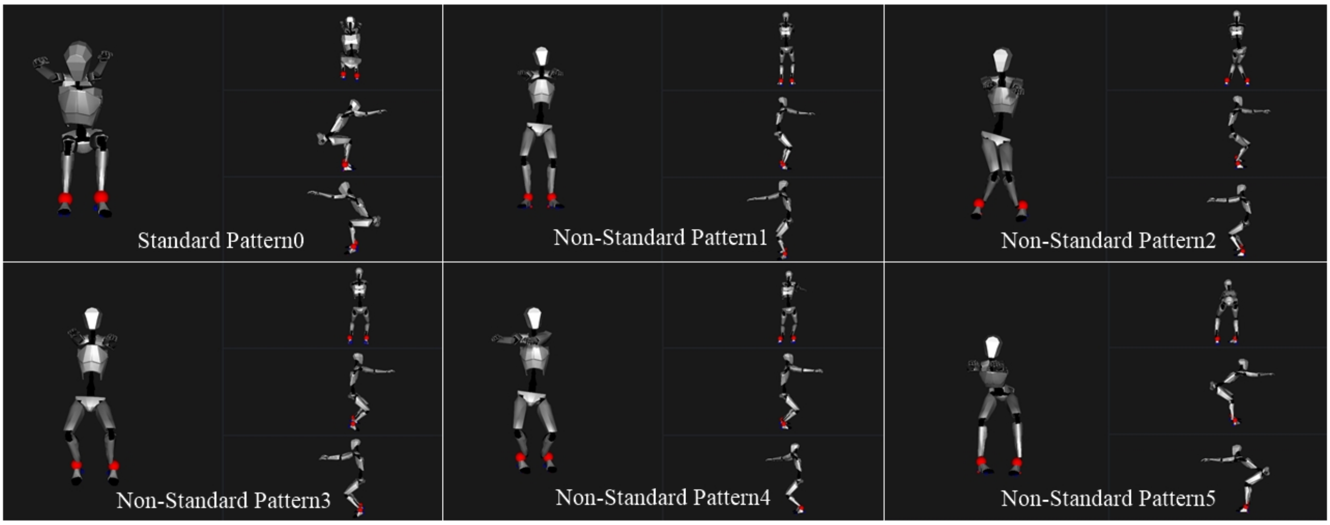

Fig. 5. Skeletons from PN that represent main phases of each squatting pattern.

Fig. 6. The interface of our squat recognition system

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