engineering proceedings

MDPI

Proceeding Paper

A game-based approach for post-stroke hand rehabilitation using hand gesture recognition on Leap Motion skeletal data†

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†Presented at the The 4th International Electronic Conference on Applied Sciences, 27 Oct–10 Nov 2023; Available online: https://asec2023.sciforum.net/

Abstract: Stroke is one of the leading causes of death and disability nowadays. Post-stroke hand rehabilitation is essential for patients to recover their hand functions. However, traditional approaches to hand rehabilitation usually involve repetitive hand exercises, which can be tedious and not engaging, leading to poor adherence of patients to the treatment plan. Recently, game-based approaches have been widely adopted to make hand rehabilitation more interactive and enjoyable. Game-based systems create an interactive environment where patients can enjoy the games while still participating in the recovery process, thus enhancing the interest and engagement of patients. Moreover, the significant growth of Artificial Intelligence and Computer Vision has led to the development of advanced hand gesture recognition techniques that could be applied in game-based systems and achieve high accuracy. This work proposes a real-time hand gesture recognition system and a gaming application for hand rehabilitation. The purpose of this work is to support and encourage patients to practice hand therapy exercises by means of interesting video games. The proposed system can recognize predefined hand gestures using the skeletal data captured by a Leap Motion Controller and then use the gestures to interact with the game environment. All the hand gestures were selected from common hand and wrist therapy exercises that are often practiced by post-stroke patients. We also conducted a user study involving 10 participants from different demographic backgrounds to evaluate the effectiveness of the system. The results showed that the proposed system is engaging and can be a potential solution to hand rehabilitation.

Keywords: hand gesture recognition; hand rehabilitation; interactive games; Leap Motion Controller

Citation: To be added by editorial staff during production.

Academic Editor: Firstname Lastname

Published: date

1. Introduction

According to some statistics in 2019 [1,2], stroke is the second leading cause of death and the third leading cause of death and disability combined, accounting for 11.6% of total deaths and 5.7% of total DALYs (Disability-Adjusted Life Years). Stroke survivors often suffer from hand and upper extremity impairment, which significantly impede their work and daily activities. Thus, post-stroke hand rehabilitation is critical for restoring hand function. This is a challenging, lengthy process, and the result depends on the stroke severity and the patients' commitment to their treatment plans. However, traditional hand rehabilitation approaches usually involve repetitive and boring exercises under a therapist's guidance, which is tedious and unengaging, resulting in poor adherence of patients. Therefore, developing an effective, engaging method to motivate patients is essential.

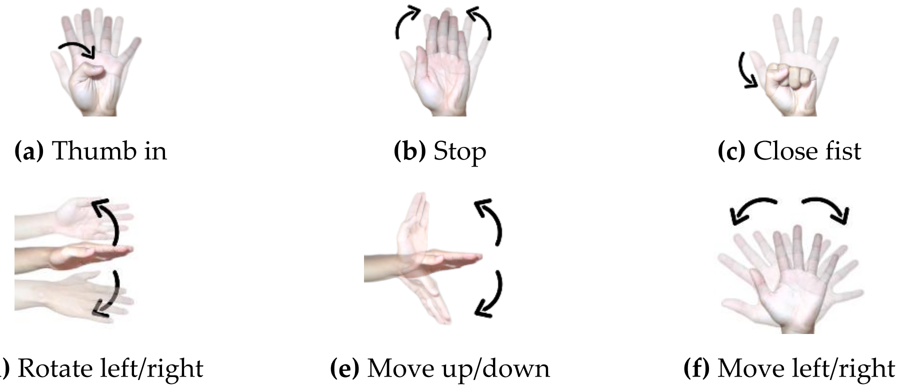


Figure 1. List of hand gestures that are selected from common hand exercises.

Recent years have seen a growing interest in game-based approaches for hand rehabilitation thanks to the development of modern technologies, including Virtual Reality [3,4], Augmented Reality [5], robust hand tracking sensors such as Leap Motion [6], and advanced algorithms for hand gesture recognition [7, 8]. Game-based approaches provide patients with an interactive and enjoyable video game environment to engage in the recovery process, offering motivating experiences that improve their adherence to treatment plans.

In this paper, we propose a real-time, skeleton-based hand gesture recognition system and a gaming application for hand rehabilitation. Our system uses a Leap Motion Controller to capture hand movement and extract hand skeletal data. We employ a pose-based approach to recognize 9 common hand gestures (Figure 1) by identifying key poses from the skeletal data. The recognized gestures are used to control actions in the game environment. All the gestures were selected from common hand therapy exercises [9, 10] which help improve hand mobility, strength and flexibility. We also conducted a user study with 10 participants, with the results showing that the proposed system is enjoyable and potential for hand rehabilitation.

2. Methods

We propose a real-time, skeleton-based approach that recognizes hand gestures based on the idea of key pose identification. The workflow of the system (Figure 2) contains three main stages: Skeleton extraction, Hand pose identification and Gesture recognition.

2.1. Skeleton extraction

In this stage, the Leap Motion Controller captures hand movement and the Leap Motion Hand Tracking Software extracts skeletal data from the user's hand. This skeletal data includes 3D coordinates of 27 hand joints in the Leap Motion coordinate system, with the origin at the device's top center. The x-axis runs parallel to the long edge, the y-axis is vertical, and the z-axis lies on the horizontal plane.

2.2. Hand pose identification

In this stage, the skeletal data captured by the Leap Motion Controller is classified into hand poses.

2.2.1. Feature extraction

From the skeletal data, 13 local features are calculated, including the Euclidean distances between palm center P and fingertips F_i, the distances between adjacent fingertips, and the angles between adjacent fingers. These features help normalize varying hand positions and angles relative to the Leap Motion sensors.

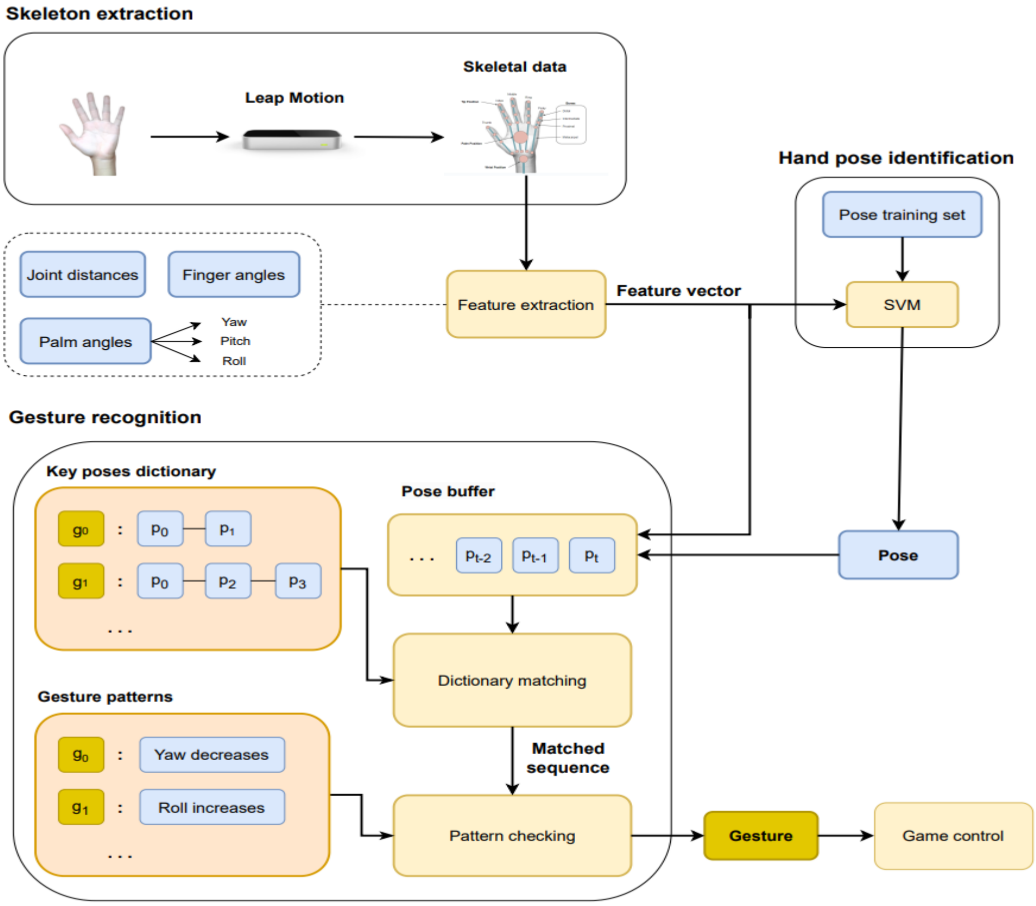


Figure 2. Overview of the proposed system. Our system extracts features from Leap Motion data and recognizes the gesture based on key pose identification.

The distance-based features are calculated as follows:

$$D_i = ||F_i - P||, i \in [1,5]$$

$$D_{Fi} = ||F_{i+1} - F_i||, i \in [1,4]$$

where Di represents the Euclidean distances between the palm center and the five fingertips, and DFi represents the distances between every pair of adjacent fingertips.

The angles between adjacent fingers:

$$\alpha_i = arccos\left(\frac{(F_i - P).(F_{i+1} - P)}{||F_i - P||.||F_{i+1} - P||}\right), i \in [1,4]$$

where α_i represents the angles (in radians) between every pair of adjacent fingers.

Next, three global features are extracted directly from the Leap Motion tracking software, including the yaw, pitch, roll angles of the hand. These features are essential to represent the movement of the user's hand during performing gestures. After feature extraction, the final feature vector V consists of 16 distinct features:

$$V = (D_1 \ldots D_5, D_{F1} \ldots D_{F4}, \alpha_1 \ldots \alpha_4, yaw, pitch, roll)$$

This feature vector is then standardized and fed to the pose classifier for hand pose classification.

2.2.2. Pose classification

After feature extraction, the feature vector is classified into one of 12 hand poses, with each pose being picked up from the set of hand gestures and serving as a component to construct hand gestures. For the pose classifier, we chose a Support Vector Machine with a radial-basis kernel function as the algorithm is suitable for small complex datasets. We utilized the One-vs-Rest strategy since it offered a fast inference speed to run effectively in our real-time system.

2.3. Gesture Recognition from Key Poses

In our setting, a gesture g is represented as a sequence of key poses $g = (p_1, p_{2,}, \ldots, p_{g_n})$, with p_i belonging to a finite set of key poses P. A key pose dictionary (Table 1) was constructed in advance, mapping hand gestures to their key pose sequences.

Table 1. Key pose dictionary for gesture recognition. Each gesture can be defined by a finite sequence of key poses.

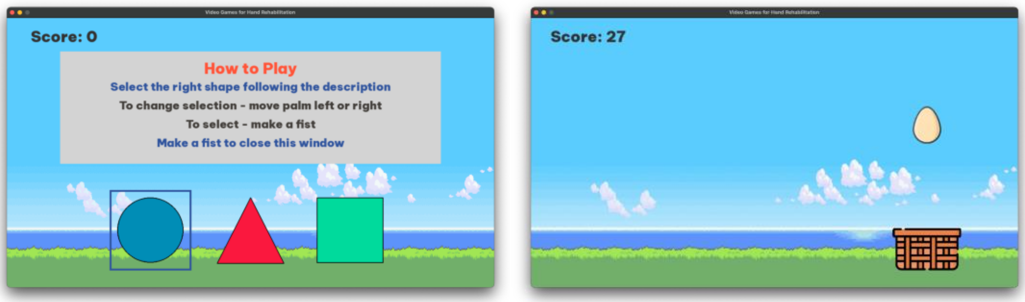
Gesture	ID	Key Pose Sequences
Move left	g_0	$(p_0, p_1), (p_7, p_1)$
Move right	g_1	$(p_0, p_2), (p_7, p_2)$
Move up	g_2	$(p_0, p_3), (p_7, p_3)$
Move down	g_3	$(p_0, p_4), (p_7, p_4)$
Rotate left	g_4	$(p_0, p_{10}, p_{11}), (p_7, p_{10}, p_{11})$
Rotate right	g_5	$(p_0, p_9, p_{11}), (p_7, p_9, p_{11})$
Close fist	g_6	$(p_0, p_5), (p_0, p_6, p_5), (p_0, p_8, p_6, p_5)$
Stop	g_7	(p_0, p_7, p_0)
Thumb in	g_8	(p_0, p_8, p_0), (p_7, p_8, p_7)

Dictionary matching: When a pose p_t is identified at time t, it is inserted into a buffer β. The system then searches from the key pose dictionary to find any key pose sequence $x = (p_1, \ldots, p_{g_n})$ that matches the sequence in the pose buffer. If there is a match, the matched gesture g will be outputted and the buffer will be emptied. Otherwise, the buffer will continue to store new hand poses.

Pattern matching: To avoid making wrong recognition, after a gesture is matched, the sequence will be validated against a set of pre-defined rules, such as the changes in palm angles or the changes in joint distances. If all the patterns are satisfied, the gesture will be transformed into an action in the game environment.

2.4. Interactive Games for Hand Rehabilitation

Upon recognizing a hand gesture, a corresponding action is sent to the game environment. We developed a gaming application with 3 interactive games: Shapes and Colors, Eggs and Milk, and Dino Run. The application is developed using Python 3.9.0 and PyGame 2.3.0. The user interface of these games is shown in Figure 3. As patients have to perform hand gestures to interact with these games, the games support them to enhance their hand functions and participate in the recovery process.



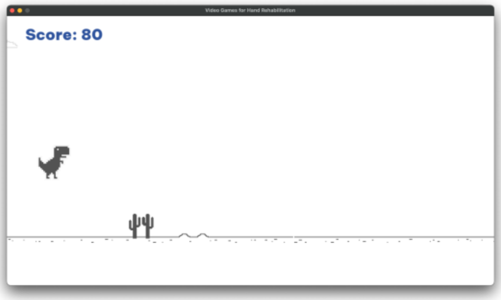


Figure 3. The user interfaces of three interactive games Shapes and Colors (left), Eggs and Milk (middle) and Dino Run (right).

3. Results and Discussion

3.1. Datasets

We collected two hand datasets on Leap Motion data - a *pose dataset* with 4396 training and 1928 test samples of 12 distinct hand poses to train and evaluate the SVM model for pose classification, and a *gesture dataset* with 438 samples of 9 gesture classes to evaluate our pose-based approach for gesture recognition. All the samples were collected by 6 subjects (4 men and 2 women) by both left and right hands, and in different ways to ensure the robustness of the datasets.

3.2. Results on Hand Gesture Recognition

All experiments were conducted on an ASUS laptop with an Intel Core i5-8250U 1.6GHz CPU and 12GB RAM to evaluate system performance on pose and gesture datasets.

We trained 5 machine learning models (SVM, MLP, Random Forest, Logistic Regression, k-NN) on the pose training set using k-fold cross-validation (k = 10) and Grid Search [11]. As can be seen from the result (Table 2), SVM achieved the highest test set accuracy (96.84%) and was chosen as the pose classifier for our system.

Table 2. Evaluation results on the pose test set of five classification models. *: The precision, recall and F_1 score is the weighted average from all classes.

Model	**Accuracy (%)**	**Precision***	**Recall***	**F_1 score***
SVM	**96.84**	0.9698	0.9684	0.9684
MLP	**96.47**	0.9686	0.9673	0.9675
Random Forest	91.34	0.9300	0.9134	0.9145
Logistic Regression	82.21	0.8336	0.8221	0.8211
k-NN	92.21	0.9323	0.9222	0.9225

After finding the best hand pose classifier, we evaluated our pose-based gesture recognition approach on the gesture dataset. The precision, recall and F_1 score on each gesture class are shown in Table 3. We achieved an accuracy of 97.95% on the gesture dataset and obtained impressive results for many gesture classes. However, there are still many false positive cases in which the system recognizes non-existent hand gestures or misclassifies a gesture as another one.

Table 3. Precision, recall and F_1 score on the gesture dataset.

Gesture	**Precision***	**Recall***	**F_1 score**
Move left	0.9796	1.0000	0.9897
Move right	0.9804	1.0000	0.9901
Move up	1.0000	1.0000	1.0000

Move down	1.0000	0.9800	0.9899
Rotate left	1.0000	0.9750	0.9873
Rotate right	1.0000	0.9211	0.9589
Close fist	0.9804	1.0000	0.9901
Stop	1.0000	1.0000	1.0000
Thumn in	0.9756	1.0000	0.9877
Weighted average	0.9903	0.9876	0.9887

3.3. Time performance

We also evaluated the time performance of the system by calculating the average elapse time per frame of the system. The result is shown in Table 4. Our system relies on the hand skeleton tracking process from Leap Motion, which operates consistently at 16.67ms (60FPS) in our experiments. Meanwhile, the execution time per frame for hand gesture recognition (1.2 ms) is significantly lower than the time required for skeleton extraction (16.67 ms). Therefore, the system's overall execution time remains within 16.67 ms (60 FPS), meaning that the system can achieve real-time performance.

Table 4. Execution time and frame per second of our system.

Skeleton Extraction by LMC		**Hand Gesture Recognition**		**Overall**	
Time	FPS	Time	FPS	Time	FPS
16.67	60	1.2	833	16.67	60

3.4. User Study

We conducted a user study with 10 individuals to evaluate our system's effectiveness. The study consists of a pre-survey stage to collect background information and a post-survey stage to collect users' feedback after trying our solution.

The pre-survey results showed that most participants were elderly or those having hand problems. Some of them had experienced hand therapy and hand-interactive games before. The pose-survey results (Figure 4) showed the overall favourable feedback of the surveyed participants, with most of them feeling that the system was compact, enjoyable, and easy to use. More importantly, all participants revealed that the proposed solution was necessary and could serve as a potential approach to hand rehabilitation.

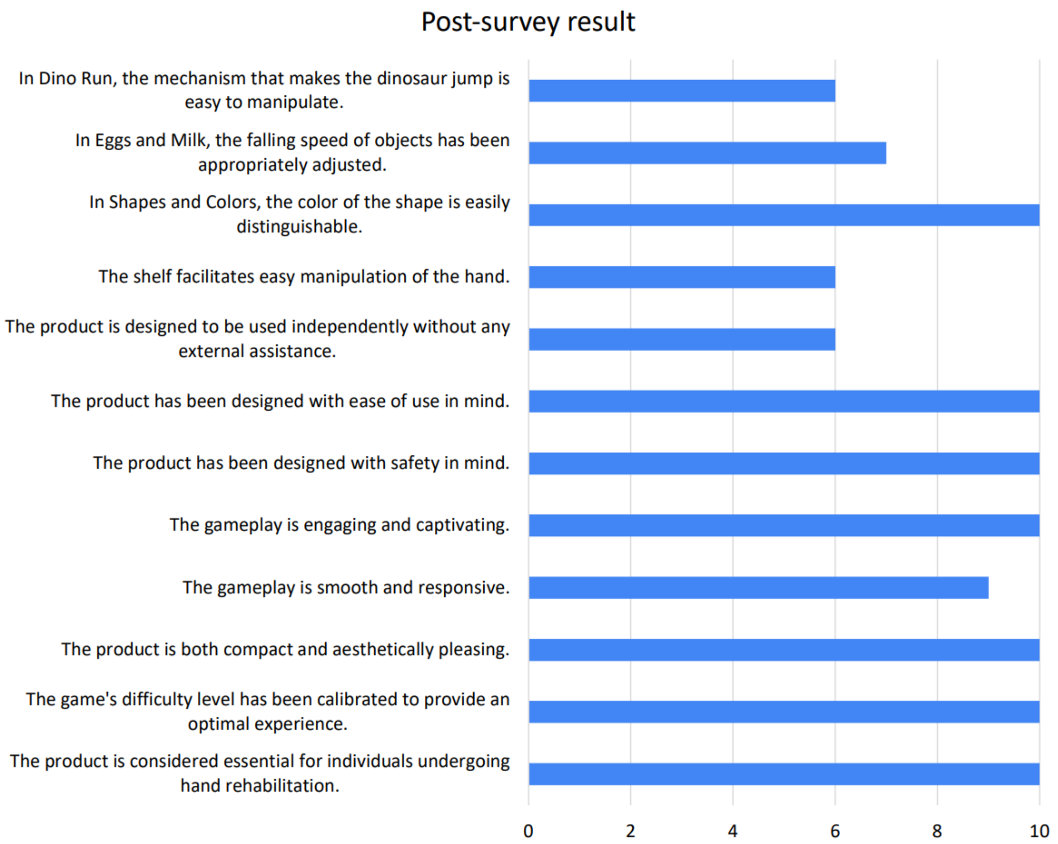


Figure 4. Result of the post-survey.

4. Conclusions

In this work, we implemented a real-time hand gesture recognition system for rehabilitation, achieving 96.84% and 97.95% accuracy on our self-generated pose and gesture datasets, respectively. We also developed a gaming application for hand rehabilitation and conducted a user study to collect feedback from real users. Most of the users agreed that our system is interesting and is a potential solution for hand rehabilitation. Our future improvement on this work includes expanding the datasets, conducting larger user studies, addressing the robustness issues, and considering alternative recognition approaches that can deal with more complex hand gestures.

Acknowledgments: The authors acknowledge Ho Chi Minh City University of Technology (HCMUT), VNU-HCM for supporting this study.

Funding:

Institutional Review Board Statement:

Data Availability Statement:

Data Availability Statement:

Conflicts of Interest:

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