A Sensor-Based Virtual Piano Biofeedback System for Stroke Rehabilitation

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Abstract— **Approximately 15 million people suffer a stroke every year globally. People with stroke usually have less mobility and this may further reduce the fitness level and emotional wellbeing. Traditional stroke rehabilitation therapy is usually performed in a clinic or hospital, which evolves the care from the therapist. Robot-assisted stroke therapy can be done at the patient's home, but the cost of the systems might be too high for some patients. In this study, we propose a novel sensor-based system for stroke rehabilitation. The system consists of a sensor-based digital glove and software running on a computer with a user interface to a piano. During the rehabilitation treatment, the patient plays the keys of a piano guided by the user interface on the screen. The system may enhance the mobility and flexibility of the affected upper limb and the fingers of stroke patients in an entertaining way. Our experimental results show that the system has a high accuracy of biofeedback.**

Index terms: Wearable sensors, Data processing, Stroke Rehabilitation.

I. Introduction

In many countries, stroke is a major disease in the elders or even some young people by frequency and cost. Using US as an example, each year the whole nation spends more than $10 billion for visiting post-stroke rehabilitation experts [1]. A stroke, sometimes refered to as a brain attack, is the loss of brain function due to disturbance in the blood supply to the brain, especially when it occurs suddenly [2]. As the affected area of the brain cannot function normally, the patients might have an inability to move one or more limbs on one side of the body, a failure to formulate or understand speech, or a vision impairment for one side of the visual field [3]. Stroke can reduce people's fitness as people with stroke usually have less mobility [4]. Reduced fitness can reduce general health level [5]. Stroke rehabilitation is a process by which the patients undergo the treatment to help them return to normal life as much as possible by regaining and relearning the skills of everyday living [6]. For most people with stroke, physical therapy, occupational therapy and speech-language pathology are the cornerstones of the rehabilitation [7].

For people with stroke who have less capability in mobility, one of the major goals in rehabilitation is to assist them to have increasing physical activities. Rehabilitation usually involves making strong movements or using normal postures [8]. Traditional methods of therapy usually involve the direct care from the therapist in a hospital or clinic environment. These interventions usually include both rehabilitation treatment as well as measurement of the rehabilitation outcomes.

Mordern electrical and computing technology has made it possible for the treatment and measurement to be done at home or in a community environment [9], [10], [11], [12], [13], [14]. For example, there are robotic devices for aiding limb movement. Tibion Bionic Leg [15] is a mobile, wearable, and intention- based robotic limb orthosis. It has force sensors placed under the foot to detect the threshold force to trigger different assistance modes according to the user's needs. The device can supply force to assist or resist leg extension and flexion. the Myomo Neuro-robotic System [16] allows the patients to make active upper extremity practice attempts with mechanical assistance. The controller consists of a fuzzy neuro-controller which is activated according to the patient's body positions. Symbiotic Terrain Robotic Assist Chair [17] features artificial touch, artificial instinct and facial feature control actions with the capability of climbing hills, curbs, and manipulating the artificial arms and metal fingers. These systems can be very benefitial to stroke patients' post stroke life quality, however, most of them are very expensive. Also, they provide more mobility for the patients but may not directly increase each body part's physical activities from the patients. In comparison, the sensor and actuator based networking system [18] is low cost and self managed. It can bring convenience and assist living for stroke patients. This inspires our research and provides a new direction for the rehabilitation research.

There are also sensor-based devices for measuring rehabilitation treatment outcome. The Smartshoe system [19], [20], [21] is an unobtrusive, wearable shoe system that can be worn at home. The sensors of the shoe can measure postures and activities, such as sitting, standing, walking time as well as gait parameters, such as number of steps and cadence, and stance. Zhang et al [22] proposed a wearable 3-axis inertial sensor to capture arm movements in 3-D space in real time. These devices measure postures and activities and have shown the potential for the patients to have rehabilitation monitoring and measurement at home. However, they cannot provide functionalities for therapy-based treatment. A system that can provide both measurement and treatment is desired by the rehabilitation community.

As stroke patients may have reduced mobility, one of the rehabilitation goals is to find suitable methods to increase their physical activities. For patients who need more activities in the upper limbs and the fingers, it is beneficial for them to have an access to musical instruments. The musical instruments, if easy to play, can serve as an entertainment method for daily life as well. As most musical instruments may be expensive and require high-level hand or finger flexibilities, people with stroke may find it difficult to have them as daily entertainment. We aim at creating a system that is low cost, easier to learn, requires less hand or finger flexibilities, and can provide encouraging words and sounds.

In this study, we propose a novel, unobtrusive sensing and feedback system. The system consists of data gloves, and the control software. Signals gathered from the glove with the information of detailed finger movement are sent to the computer through WiFi. The software has a user interface including three components: The first one is a piano image with keys that can be marked out when being pressed on. The second one is the instruction notes with the information of which fingers to use to play the key. The last one is the score and the comment displayed as text. Participants wear the data gloves and follow the notes displayed on the screen. The system can provide feedback for the performance and a record of performance for each run. The whole sysem is light-weight, inexpensive, and is feasible for everyday usage with the goal of increasing up-limb activities and finger flexibilities in the home.

II. Methods

A. System Overview

The whole training can be done in a home environment. The person in the training may not have the mobility of lower limbs. For example, the participants may be sitting in a wheelchair, or in orthotics standing with no movement involved. People in the training move hand and fingers according to the notes displayed in the computer. The performance of the user can be recorded and analyzed by the software program. When the person performs correctly, the software can play the sound of the keys which contribute to a whole piece of music with the audio feedback. The software also provides visual feedback including the image of a piano with marked keys and comment messages. These comment messages include a score recording the number of correctly played keys and a text message. The whole system was designed with C++ programming language. The preliminary test was done with a personal computer with 2.4 GHz CPU and MS Windows operation system. Figure 1 shows the architecture of the whole system. The following sections will describe the design of the system. Section B introduces the wearable glove sensors. Section C describes the Data handling program. Section D illustrates the key identifier program. Section E is about the error correction rules. Section F describes the notification generator program. Section G illustrates the data collection and validation methods.

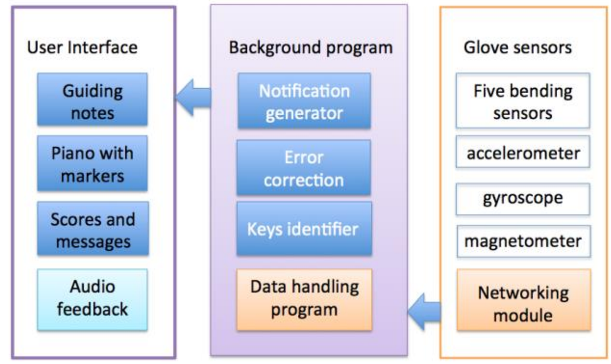

Figure 1. The architecture of the system.

B. Wearable glove sensors

We utilize data glove DG5-Vhand (DGTech Engineering Solution) for data collection. The glove has five bending sensors attached to the fingers and a box with integrated circuit inside. The box is attached to the back of the hand. In the box there are three different embedded sensors: a gyroscope, a magnetometer and an accelerometer. These sensors have high sensing resolution and make it possible to compute hand position parameters, such as roll, pitch and yaw. The sensor configuration enables the hand sensing system able to sense the hand position, movement status, as well as finger positions. The data aggregated is sent to the computer through USB or WiFi. The WiFi configuration makes it possible for multi-glove to operate simultaneously with a high data rate. With one glove, the data throughput rate can be 1Mbps with TCP/IP and WPA2.

C. Data Handling Program

The data handling program includes two parts. One is the data aggregation program and one is the data checking program. The data is sent through WiFi to the computer from the data glove. Thus on the computer side, the data aggregation program includes a socket to get the data through TCP/IP. The data is sampled at 5 Hz and the accumulated data is used by the program in real-time. It is saved in a .txt file for further usage. The data checking program includes a Decision Tree classifier to check whether the user is performing the targeted task. The classifier has two classification results: one is playing piano, and the other is resting.

Firstly, we collect data from the participants with the above two activities. The detail will be described in Section F. Then the classifier is obtained through the training process. The training of the Decision Trees classifier is performed in a hierarchical style, and recursively separates the input space into class regions. We utilized C 5.0 algorithm in our program. The result is a tree-like structure, which is composed of decision nodes and leaves. Each node has a test function that determines which branch is taken for the next step. This process is repeated until one of the leaves is reached and therefore a decision is made. Figure 2 shows the data handling procidure.

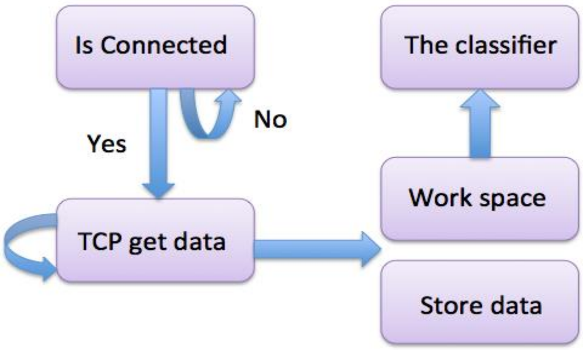

Figure 2. Data handling procedure.

D. *Key Identification Algorithm*

The key identification algorithm is used to identify whether a key is pressed or released. The data used as the input of the algorithm is the readings of the bending sensors attached to the five fingers. The signals $BS_i(t)$ represents the 5 bending sensor readings. The key identification procedure was performed in two steps. First, we pre-collected a dataset when the user is playing a piece of music possibly with each finger bended occasionally. With this dataset, we used an algorithm to compute a threshold T, which is the decision bound to determine whether a key is pressed or released. Then we designed the algorithm, which runs in real-time to identify which keys are pressed or released.

The pseudo code for the above two steps is shown in Figure 3. The first algorithm computes the threshold, and the second one is for the identification of the keys. To compute the threshold, we firstly seek vectors of local maxima and minima and compute the average value of the vectors. The threshold T is defined using these values. In identification of the keys, we utilized the computed threshold for each of the bending sensors BS_i. The determination of the values of the key_start and key_finish is made by examining the gathered sensor readings. When the waveform up-crosses the threshold, the key_start has the value 1. When the waveform down-crosses the threshold, the key_finish has the value 1. These parameters control whether to send control messages to the user interface to trigger the visual and audio feedbacks.

for i=1: 5
    vector_min$_i$=find_local_minimum(BSi(t));
    vector_max$_i$=find_local_maximum(BSi(t));
    $\overline{min}_i$***= mean(vector_min$_i$);***
    $\overline{max}_i$ ***= mean(vector_max$_i$);***
      Ti = $\overline{min}_i + 0.4*(\overline{max}_i - \overline{min}_i)$;
end

Part 1. Pseudocode for computing the threshold.

for i=1: 5
    if ($BS_i(t) > T_i$) &&($BS_i(t-1) < T_i$)
        key_start$_i$ = 1;
    else
        key_start$_i$=0;
    end
if ($BS_i(t) < T_i$) &&($BS_i(t-1) > T_i$)
        key_finish$_i$ = 1;
    else
        key_finish$_i$=0;
    end
end

Part 2. Pseudocode for identification of the keys.

Figure 3. Pseudocode for Key Identification Algorithm.

E. *Error Correcting Procedure*

To make the system easier to access, we have an error checking procedure which aims to reduce the difficulty level of using the system. We have several rules to achieve this goal:

- If a particular key is pressed longer than the pre-defined time T_standard, we set the parameter key_off to 0. This can prevent the continuous display of sound caused by a particular finger not positioning well.
- If two keys are pressed at the same time, we only mark the correct one for notifications. This can avoid the situation where the nearby keys were likely to be pressed at the same time.
- If a particular key is incorrectly played more than 5 times, we send the notification to play the key and thus the whole music may be played continuously without getting stuck at a particular note.

F. *The Notification Triggers*

Once the keys are pressed, we send notifications to trigger the visual and audio display in the user interface. Firstly, we generate piano feedback. This includes the maker on the pressed keys and the corresponding music for them. Generally, the length of displaying the maker and the output sound are determined by the time that the key is released. However, in certain cases, the error correction algorithm also works for determining the release time of the keys. Secondly, when the keys are correctly displayed, the score function is called to display a score with an increase of 1. The score keeps adding up for a user unless it is reset to zero by the user. When the user plays five notes correctly and continuously, the message function will be called to display a message, for example 'Great job'.

G. *Data collection and validation methods*

As a preliminary study the data collection was performed on three healthy adults. Two of them had no previous music instrumental playing experience. One of them had piano playing experience for more than 10 years. The data collection was done in two steps. The first step is to collect data for training. The three subjects played the target piece of music for five times each and rested for same length of time after each term of play. The data collected was used for training the classifier in the data handling process and computing the threshold in key determination process. The second step was to collect data for validation. The user played the music for five times each and then rested for a self-selected time. A total of 56 minutes of data were collected.

Validation of the data analysis results was carried out with the help of an video camera. Both the hand position and finger movements and the feedback interface were recorded with audio and visual images. An expert with specially knowledge of data anlysis and and the skill of piano performance manually recorded down the correct and incorrect presses of the keys. The validation results were calculated based on the records.

The feedback events were counted as true positives (*TP*), false positives (*FP*), and true negatives (*TN*) and false negatives (*FN*) depending on whether the feedback was expected for a given activity. The counts of *TP*, *FP*, *TN* and *FN* were used to estimates the sensitivity and specificity of the feedback mechanism:

$$Sensitivity = \frac{TP}{TP+FN} \quad (1)$$

$$Specificity = \frac{TN}{FP+TN} \quad (2)$$

III. Results

Figure 4 shows the user-interface of the system. The numbers displayed above the keyboard is the guiding notes which show which finger needs to be bended. The keyboard displays a marker when the correct key is pressed. Below the keyboard is the score of correctly played notes numbers as well as the message on the comment of the performance. A marker on the keyboard is displayed at the same time when the audio sound is played.

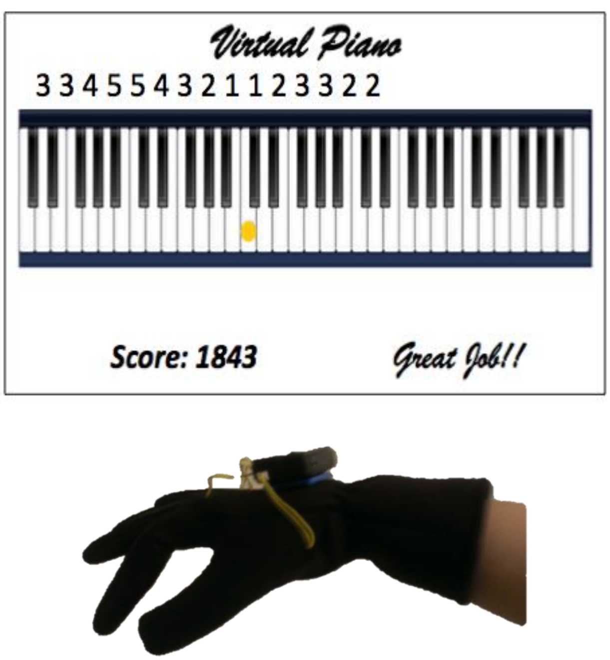

Figure 4.The user interface of the system.

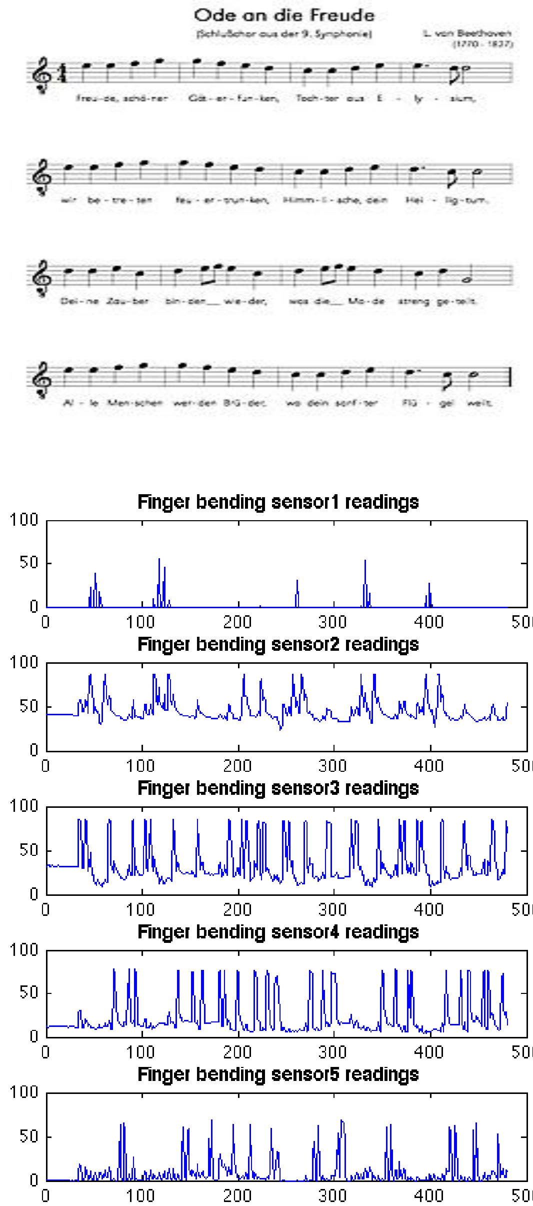

Figure 5.The music sheet (upper) and the corresponding sensor readings (lower).

Figure 5 shows a music sheet and the corresponding sensor readings when the person played correctly. In this study, this music sheet in Figure 5 upper is particularly chosen for the design. The reason is as the follows: First, the music is classical and cheerful which may enhance the user experience. Second, the notes are easy to play with only one hand. Also the music has notes scattered well for play convenience of all five fingers. This will enable the user to have the chance to practice with all the fingers. The digital glove is shown below the display screen. We can see that it is minimum obtrusive and convenient to wear.

Table I shows the confusion matrix of the classifier in the data handling procedure. We can see that the classifier has a high accuracy of recognizing whether the user is performing the proposed task or resting.

TABLE I. CONFUSIOIN MATRIX OF THE DECISION TREES CLASSIFIER

Classified as →	Playing	Resting
Playing	4860	72
Resting	432	4500

From Table I, we can see that very few play activities are misclassified as resting and more resting activities are misclassified as playing. This is because when performing the resting activity, the participant performs their self-selected activities. The hand position and the movement of fingers may be very similar to the ones in playing.

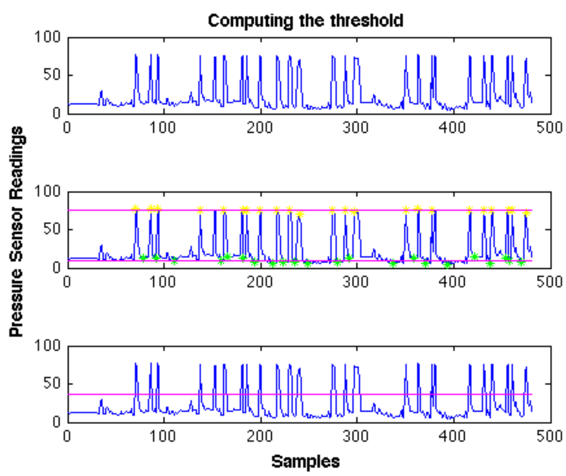

Figure 6. Computing procedure to define the threshold for key identification.

Figure 6 shows the threshold for key pressing or releasing identification. The first plot is the original bending sensor readings from one finger. The second plot shows the local maximum and local minimum values and the average of them. The third plot shows the threshold that is defined.

TABLE II. COUNTS OF TP, TN, FP, AND TN DURING THE EXPERIMENTS

TP	FP	TN	FN
835	22	57	16

Table II shows the computation accuracy of the software. We can see that most of keys can be identified correctly by the software. The precision and recall are 98.12% and 72.15%. Some incorrectly played keys are identified as correct ones. One reason for this is that the error checking algorithm increases the chance of a song played continiously.

IV. CONCLUSION AND DISCUSSIONS

In this paper, we proposed a novel virtual piano biofeedback system for stroke rehabilitation. The system is minimum obtrusive and can provide entertainment for the users. The system can run in real time and has a high accuracy of identification of the keys played. Stroke affects one side of the body more often than not. In this paper, to get a song correct, the music only needs to be play with one hand. It will be useful to extend the system to be played with both hands as it may help with training for hands coordination for stroke patients.

Further study also includes recuiting stroke patients as participants. We plan to listen to their suggestions to gain knowledge about how to improve the system.

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