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A NEURAL NETWORK FOR RECOGNIZING MOVEMENT PATTERNS DURING REPETITIVE SELF-PACED MOVEMENTS OF THE FINGERS IN OPPOSITION TO THE THUMB

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A data glove is a typical input device to control a virtual environment. At the same time it measures movements of wrist and fingers. The purposes of this investigation were to assess the ability of BrainMaker™, a neural network, to recognize movement patterns during an opposition task that consisted of repetitive self-paced movements of the fingers in opposition to the thumb. The neural network contained 56 inputs, 3 hidden layers of 20 neurons, and one output. The 5th glove '95™ (5DT), a commercial glove especially designed for virtual reality games, was used for finger motion capture. The training of the neural network was successful for recognizing the thumb, the index finger and the ring finger movements during the repetitive self-paced movements and neural network performed well during testing.

Key words: virtual reality, neural network, measurement method.

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INTRODUCTION

In the past few years virtual environment (VE) technology has undergone a transition (1) that has taken it out of the realm of expensive toy into that of functional technology. Up to now the use of VE was focused mainly on applications for surgery and military simulations. Recently, in the field of Mental Healthcare, the considerable potential of VEs has been recognized for scientific study, assessment and rehabilitation of a wide range of mental disorders and functional impairments (2, 3). A European project, the VREPAR (Virtual Reality Environment for Psycho-neuro-Assessment and Rehabilitation) (4) has shed a new light on the use of virtual reality in neurorehabilitation (5).

A number of today's technological problems are in areas where neural network technology has demonstrated potential: things like pattern recognition and classification, speech and image understanding, robotic controls, sensor processing, optimization and learning. This growing power of handling information allows e.g. on-line patient databases (6), remote consultation (7) and the use of robots for rehabilitation (8, 9). A neural network simulator is a program that creates a model of artificial neurons and the connections between them and then trains this model. Neural networks, just like people, learn by example and repetition. At a fundamental level, all neural networks learn associations. With a medical neural network, all you have to do is show it the related data for patients with the disease and data for those without the disease; the network will figure out the subtle relationships in your data. In that way a trained network can recognize e.g. abnormal movements (10). Once the network 'understands' what 'abnormal' means, it can either adjust movements by manipulating the created virtual environment or guide the patient directly through impedance-controlled resistance. A data glove is a typical input device to control a virtual environment. At the same time it measures movements of wrist and fingers (11). As such, it provides an important role for the evaluation and treatment of abnormal movements in patients.

At the moment different kind of data gloves are available. Some of them are restricted to professional virtual reality laboratories and therefore are rather expensive. Other gloves that are designed exclusively for games are cheaper but make no pretensions to expert knowledge in the rehabilitation field.

The aim of this study is to evaluate if a neural network can be trained by the data flow of a commercial data glove to recognize movement patterns during an opposition task that consisted of repetitive self-paced movements of the fingers in opposition to the thumb. This kind of finger exercise is often used as a quick evaluation of dexterity and functional performance in patients recovering from stroke. The typical displacement and speed profile of each finger in relation to the others during this task is a prime requirement for advanced prehension.

METHODS

Instrument

The 5th glove '95 (version 1.00, 1996) (Fig. 1) is a data glove that can measure pro/supination of the forearm and flexion/extension of the fingers and wrist. Only flexion and extension of the fingers were taken into account for this study. The sensors for flexion and extension are based on an optical fiber technology. Each finger is fitted with one sensor, which measures the average flexion and extension of that finger. Each sensor provides an 8-bit resolution (i.e. 256 positions). The optic fibers are stitched into the elastic Lycra tissue of the glove. The 5th Glove '95 connects to a standard 9-pin RS-232 serial port. This serial connection will allow the computer to communicate with the device. The data glove has an external 9V power supply. The data glove starts up in command mode. This mode accepts and transmits serial information using 19200 baud, 8 bits, 1 stop bit, and no parity. The serial link only utilizes the TX (transmit), RX (receive) and GND (ground) lines. A

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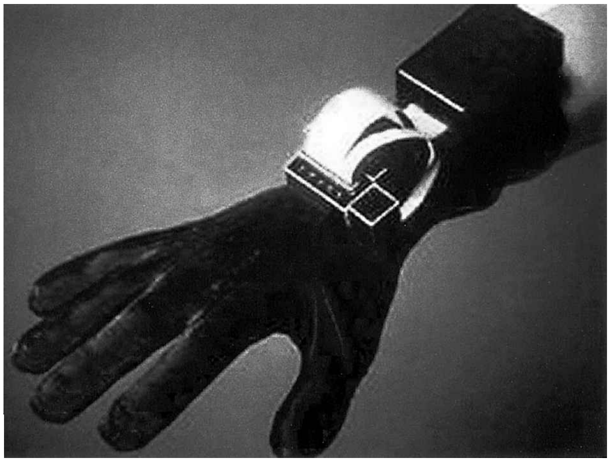

Fig. 1. The 5th glove '95™. Fifth Dimension Technologies. Pretoria, South Africa.

computer program (Glovestat) is constructed to record and save numerically the flexion and extension of the fingers. The sampling rate was 95Hz. Dasy*lab*™ (Version 200.10 Dasytec™) was used for the graphical representations of the data. Examples of printouts are shown in Fig. 2.

BrainMaker™ (California Scientific Software) performed the building, training and testing of a standard back-propagation neural network. Back-propagation is a supervised learning method in which an error signal is fed back through the network, altering weights as it goes, to prevent the same error from happening. BrainMaker™ was run under DOS 6.0 on a PC-486 with 8Mb RAM.

Design and subjects

The study comprised 66 subjects (41 women and 25 men). The mean age ± SD was 47 ± 18.1 years, range 21–86 years. Two women and one man reported left-hand dominance. All subjects included were volunteers with no signs of disease or injury. The subjects had to perform an opposition task that consisted of repetitive self-paced movements of the fingers in opposition to the thumb. They were asked to do this as accurately and rapidly as possible during 20 seconds. The signals coming from the 2nd and 4th finger sensors had a poor quality and were therefore excluded from further analysis. The procedure was repeated after 30 minutes. On comparison, the difference between both measurements turned out to be fractional and the procedure showed a high test–retest reliability for the thumb, the index finger and the ring finger. No gender differences were found. The overall performing speed was slightly slower for the oldest subjects (unpublished data), but this was non-essential for training the neural network in view of the information on which the neural network based its predictions, generalizations or recognitions.

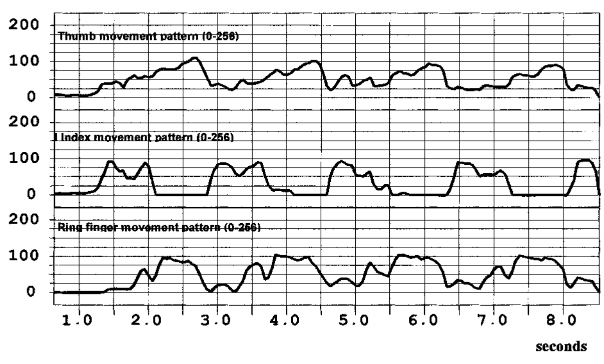

Fig. 2. Graphical representation of movement patterns during an opposition task that consisted of repetitive self-paced movements of the fingers in opposition to the thumb. Above: thumb; middle: index finger; below: ring finger. X-axis: time in seconds. Y-axis: position (minimum = 0, maximum = 256 (8 bit resolution)).

Measurement procedure

The subjects were seated close to the table with the elbow on the table. The subjects were asked to put on the glove. The glove was tightened to fit the subjects' hand.

Next the shoulder joint was positioned in 20–25° and the elbow joint in 90–95° of flexion. The wrist was held at the middle course of pronation and supination. During a brief period the subjects were allowed to try the movement. Then the experiment was started.

Analysis

For each finger a random snapshot of 3 seconds was taken from the 20-second recording. The onset of this snapshot coincided always with the initiation of the pincer movement between the thumb and the index finger. The strips were brought into the neural network. This network contained 57 input nodes (19 × 3 seconds), each node representing one of the 19 selected values/second (±1 value each 0.053 second). There were 3 hidden layers of 20 neurons and one output neuron representing the name of the pattern (the thumb, the index finger or the ring finger). The number of neurons in the hidden layers was calculated according to the following rule: Input + Outputs/2. This resulted in 29 neurons. In the case of several hidden layers the number has to be decreased by around one-third. This resulted in the use of 20 neurons. Implementing too many neurons in the hidden layers has the disadvantage that the network memorizes the data without understanding the meaning behind the data structure. No learning will be achieved and, as such, the network will not generalize.

Usually, the more facts you collect, the better the network can be trained. Accordingly, the data obtained from test and retest was put together. By doing so 396 examples (2 × 3 finger × 66 subjects) were entered into the network for learning. BrainMaker automatically set an at random sample of 40 examples aside for testing the network on data it has never seen before. Neural networks are often sensitive to the order in which the training facts are presented. If training facts are highly ordered, or grouped in a non-random way, BrainMaker may have more difficulty learning patterns. Mixing up, or randomizing, the order of the facts before training will force the network to generalize over the entire training set (12). Therefore the computer shuffled the training facts 4 times. The learning rate specifies how large a correction BrainMaker should make when there is a network error. A learning rate of 1.00 was used which is usually safe and a good place to start. By default, the value of the smoothing factor was 0.9 and each individual layer's value was 1.0. The smoothing factor determines how much of the error correction will be made at the time the error is encountered and how much will be averaged into successive runs. For each layer of the network a sigmoid neuron transfer function was used. This curve approaches a minimum and maximum value at the asymptotes. Mathematically, the exciting feature of these curves is that both the function and its derivates are continuous. This option works fairly well and is often the transfer function of choice (13). Training error tolerance and testing error tolerance specify how accurate the neural network output must be to be considered correct. This error tolerance can be specified to BrainMaker in terms of a percentage of the output range. For example, if the output value can be anything from 0 to 100, the range is 100. A 0.05 error tolerance is equivalent to 5 (5% of 100) (14). In this study no corrections were made to the network during training if all the outputs were within a tolerance of 0.05. During testing, errors are reported for facts outside a testing tolerance of 0.1. Learning stopped when 90% of the answers were correct.

RESULTS

The training of the neural network was successful. After 11 minutes of training, the network learned the movement pattern generated by the thumb, the index finger and the ring finger during an opposition task that consisted of repetitive self-paced movements of the fingers in opposition to the thumb.

The network performed well during testing and made a high score. Of the presented 40 unknown test cases, 32 out of them were recognized correctly by the network as the movement pattern of the thumb, the index finger or the ring finger.

DISCUSSION AND CONCLUSIONS

Conventional evaluation of many neurological and musculoskeletal disorders involves the examination of movement. The examination of a subject's hand function, in particular, is a central part of visual diagnostic procedures.

The purpose of this article was to investigate the feasibility of integrating neural nets into a virtual reality data glove. The major objective of applying virtual reality and associated technologies to rehabilitation is to enhance diagnostic and therapeutic activities in a range of medical fields by allowing a medical expert team the opportunity to view and analyze movement patterns as they happen in a controlled environment (15). Because of their massive parallelism, neural nets can process information and carry out solutions almost simultaneously. If a problem involves recognition or classification, a neural network will do it faster, more consistently, and better than a person. These findings are in line with results obtained in Parkinson patients. Gloves were used to quantify tremors (16) and an automated form of video image analysis was successfully applied to classification of movement disorders (17).

In skilled hand activities, the specificity of the muscle activation pattern determines whether a patient can grasp an object or not. A neural network tested for finger movement recognition can be placed on a chip, which is then placed into a glove's electronics that control data flow to the chip, rather than having software control the data flow. The operation becomes so much faster that during a hand rehabilitation session neural networks can control processes as they happen, which is known as real-time operation. The idea is that under these circumstances connections among perceptual and motor groups of neurons can interact with each other and almost simultaneously with new information from senses, without the intervention of a therapist that summarizes and interprets the information (18). While this technology appears to offer many advantages for rehabilitation applications, the first step for such program is for the developer to perform a realistic cost/benefit analysis (19). This is the reason why this study used a commercial and affordable data glove for testing its usefulness in neurorehabilitation. Our study proved that a neural network was capable to recognize movement patterns generated during pincer movements.

A major problem of the 5th glove is, that it is only available in one size. This is probably the cause of the poor results obtained from the second and fourth finger. Indeed, if only those subjects were considered in which the glove fit at best, no problems were found for the mentioned fingers. Another plausible explication is that some persons have been using an adduction–opposition strategy during the thumb–fourth finger test. The glove cannot sense this movement. An important drawback is that only an average flexion–extension of the fingers is measured. This makes the glove in its actual design unsuitable for recognizing and adjusting very complex movements such as palmar prehension, commonly used to grasp small objects and for many skilled hand activities. Unfortunately, many patients with a brain injury never reach the advanced recovery stages during which complex finger coordination becomes possible and it must be kept in mind that for those patients the glove can play a part in the rehabilitation of lateral prehension, cylindrical or spherical grasp.

A fundamental issue that has important implications regarding the ultimate utility of these new therapeutic approaches for rehabilitation is the concept of generalization of this treatment. As VEs are developed to treat patients, it will become imperative to demonstrate that the results have some relevance or functional impact on users' real world behaviour (20).

Although the application of virtual reality appeals strongly to patients and physicians, the institutional and implementation barriers have proven formidable, and progress is slow.

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