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# ENHANCEMENT OF VR-DATA GLOVE GESTURE LIBRARY USING ARTIFICIAL INTELLIGENCE

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## ABSTRACT
*Virtual Reality technologies are nowadays broadly applied in production engineering. There is an increasing number of VR simulations which, beside conventional, also use the gestural interface which requires an operator to wear a VR data glove. Ergonomic and mnemonic features of the gesture library are of utmost importance for efficient application of any data glove. For that reason, an AI-based neural network software module was developed for the 5DT Ultra 5 data glove. This module allows two key advancements: (i) extension of the standard library of gestures and (ii) more reliable interpretation of the newly developed and standard gestures.*
**Keywords:** Virtual Reality, Artificial Neural Networks, Data Glove

## 1. INTRODUCTION
VR data gloves have been used for nearly two decades as the standard input device for VR applications. Due to their broad applicability, they are nowadays used in popular computer games as well as in serious VR simulations – from medicine and psychology, to a vast array of industrial applications [1]. Though their design and construction allow dexterity of human hand to be put to full use, data gloves have been plagued by steep prices and varied performance reliability, i.e. gesture identification. Even today, the development of software solutions which allow reliable and efficient gesture identification is still in its infancy, with a number of contributions using various approaches to remedy the problem.

## 2. PROBLEM DESCRIPTION
Due to its all-round characteristics and a relatively low price, 5DT Ultra 5 data glove (Fifth Dimension Technologies) is very popular amongst both industry professionals and researchers. The glove is equipped with five proprietary optical sensors which allow it to measure finger flexure using one sensor per finger. It also comes with a ready software support for the detection of the predefined set of 16 gestures. However, the glove is not suitable for use with MCAD without some important modifications, namely:

- only a third of the predefined gesture set are ergonomically suitable for prolonged use, since they cause muscle fatigue;
- though thumb flexure is measured, none of the standard-library gestures include the use of thumb, which not only prevents the simulation of grasping but also makes it impossible to simulate useful gestures which require the use of thumb;

- owing to the ergonomic issues and the principles of operation of the optical sensors, the gestures are sometimes misinterpreted or undefined;
- most of the gestures lack symbolical meaningfulness which is necessary for efficient use with MCAD applications.

The standard gesture library can be extended with additional gestures to remedy the stated problems. Figure 1 illustrates the six gestures which include the use of thumb and are presently not part of the standard gesture library of the 5DT Ultra 5 data glove.

In order to provide proper software support for the new set of gestures, two approaches are possible – the classical programming method and the method based on artificial intelligence. The second method is practically applied and documented in [6] and is also chosen in this work, due to greater reliability and flexibility in comparison with the classical programming method.

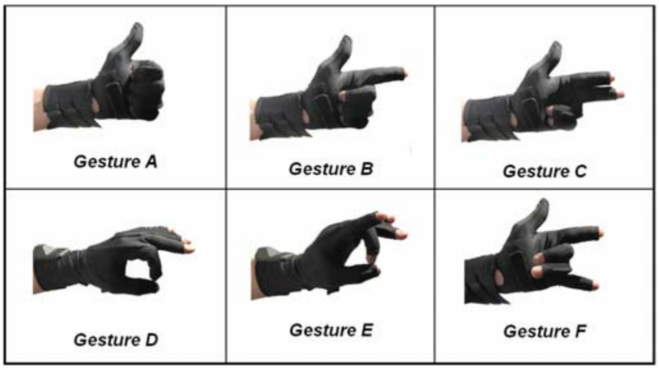


*Figure 1. An extended set of gestures which employ thumb for 5DT Ultra 5 data glove*

## 3. MOTIVATION FOR APPLICATION OF ARTIFICIAL NEURAL NETWORK

The standard gestures supported by 5DT Ultra 5 are coded as a combination of binary open-closed states for four fingers – thumb excluded. It is thus possible to make $2^4=16$ combinations of open and closed fingers, which equals the total number of possible gestures [2]. The gestures are designated 0-15, with the “0” gesture representing “fist” (all fingers closed) and the “15” gesture representing “palm” (all fingers open).

If the finger sensor reading is above the predefined upper boundary, the finger is considered closed. Conversely, if the sensor reading for the finger is below the lower boundary value, there is no flexion detected and the finger is considered open. In the case of all other possible values falling inbetween the two boundaries, error signal is emmitted, i.e. such gesture is considered undefined [2].

This conventional method of gesture identification yields good, but not always reliable results. The main reason for that is to be found in the anatomy of humand hand, as well as in the sensor layout. For that reason, the so called sensor coupling occurs during gesture execution, which is the frequentcause to missinterpretation of correctly executed gestures [3].

There are two basic reasons which motivated the authors to apply an artificial neural network (ANN) in this work:

- to allow the use of a custom-designed, extended set of gestures which would be adjusted to application in a VR-based MCAD application.
- to interpret the 16 gestures from the standard gesture library, as well as the new gestures, with higher reliability as compared to the, previously described, conventional method;

## 4. ANN ARCHITECTURE, TRAINING AND TESTING

### 4.1 ANN architecture

Typical areas of application of artificial neural networks (ANN) are classification, aproximation and mapping tasks. Of crucial importance are the quantity and quality of input training data, since ANN are unable to generate information which are not contained within the input set. Extensive discussion of application of various types of ANNs for data glove input detection can be found in [5].

The ANN model was realized and tested in Matlab Neural Networks Toolbox. The ANN used was a two-layer *tansig* and *log-sigmoid* network [4] (Fig.2).

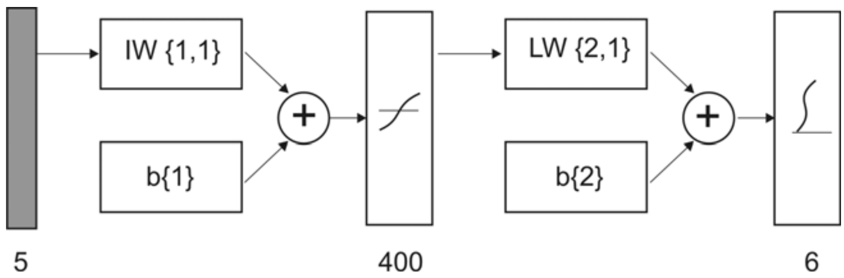


*Figure 2. Architecture of the two-layered ANN used in the experiment*

For every gesture the network was fed a 5 element input vector. The number of neurons in the hidden layer was subject to experimentation, so the final version of the network comprised a total of 400 neurons.
Upon completion of the training process, the network was required to correctly identify the gesture by responding with the output vector.
Variable learning rate was used, which means that the optimal learning rate changed during the training process in order to adapt to the complexity of the local error surface.
The correct answer was the vector containing a 1 in the position which corresponded to the number of the input gesture.

### 4.2 ANN training and testing

The network training was performed in three phases.
During the first phase, the network was trained with 6 ideal input vectors (without noise). The stopping criteria were either completion of 10,000 epochs or achievement of the sum-squared error below 0.1, whichever came first. This phase was successfully concluded by meeting the sum-squared criterion after a total of 129 epochs.
After the first training phase, the network was tested and it performed well, correctly classifying ideal input vectors for gestures A, B C and F (Fig.1). However, gestures D and E (ring configuration with the thumb and the index finger, i.e. the thumb and the middle finger) were not identified correctly due to similarity of the gestures, i.e. the input vectors which represent them (Fig.3).
The second training phase included training with 2 ideal input vectors and a total of 30 noisy input vectors representing the 6 experimental gestures. The noisy vectors were divided into 3 *series of* 10 vectors, each series generated with the different level of white noise. White noise was generated programmatically, using arrays of random numbers with mean 0 and different standard deviations (σ). The relevant data are shown in Table 1.

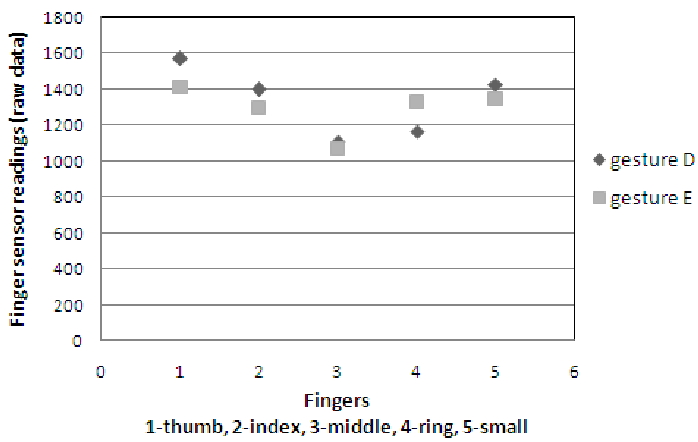


*Figure 3. Similarity of gesture data for gestures D and E*

*Table 1. Parameters for noisy input series $I_{1-3}$*

| | $I_1$ | $I_2$ | $I_3$ |
|---|---|---|---|
| Mean ($\bar{x}$) | 0 | 0 | 0 |
| St.dev. ($\sigma$) | 270 | 280 | 285 |
| Error goal (sse) | 0.5 | 0.6 | 0.6 |
| No. epochs | 1000 | 2000 | 2000 |

Upon completion of the second training phase, the network was tested once again, this time with noisy input vectors. The network responded well, this time correctly classifying and identifying gestures D and E, as well as the four remaining gestures, A, B, C and F.

Finally, in phase three a repeated training with ideal input vectors was performed to insure that the ideal input detection is uncompromised with the previous training phase which used the noisy vectors.

## 5. ANALYSIS OF RESULTS

Training with ideal input vectors allowed gestures without noise to be interpreted with success rate of 67%. The lower rate was due to network inability to properly classify two similar gestures, D and F (Fig.1).

This problem was remedied by the second phase training with noise. Upon completion of this phase, the network was able to identify gestures D and F with a success rate of 87% while the success rate of for gestures A, B, C was 98%.

In order to bring the detection rate for gestures D and E to the desired level of 95 -98%, the number of neurons in the hidden layers should be increased and the training should be extended with an additional set of noisy input vectors.

## 6. CONCLUSION

Application of artificial neural networks in data glove gesture recognition not only allows a more reliable detection of the predefined, standard-library gestures, but also enables data glove to be efficiently used with an extended set of gestures. In the case of the 5DT Ultra 5 data glove, that includes gestures which use the thumb as the fifth finger, without which it is impossible to use this glove in VR simulations which require "grasping" of virtual objects.

In this experiment, the noisy input vectors used for training were programmatically generated in Matlab. Training with noisy input allowed the network to properly identify even the gestures with very similar input vectors.

The next phase of investigation shall include a more realistic approach, meaning that the ANN training shall be conducted using a set of input vectors recorded from several male and female users, which would allow the network to more flexibly respond to variations in input vectors which are the result of anatomical differences between various users.

The results obtained show that, given proper software support, 5DT Ultra 5 data glove can be efficiently used with various VR and MCAD-related software applications with various configurations of low-budget VR workstations. This should allow a wide-spread application of virtual technologies in both production engineering-related academia and industry.

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