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Data Prediction of Optical Head Tracking using Self Healing Neural Model for Head Mounted Display

A Kataria[1], S Ghosh[1]* and V Karar[2]

[1]Department of Electrical and Instrumentation Engineering, Thapar Institute of Engineering & Technology, Patiala, 147004, India

[2]Optics Devices and Systems, CSIR-CSIO, Chandigarh, 160030, India

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Helmet Mounted Display (HMD) is an essential part in field of avionics. It is worn by the pilot to sight the external environment along with synchronized view of the important parameters of the airplane on its visor. To achieve the perfect synchronized view on the visor of HMD, the coordinates of the external environment and the coordinates of the pilot's head motion should be in proper synchronization. To acquire the coordinates of the pilot's head motion, the head tracking process is involved. Head tracking can be done using different tracking techniques such as Optical tracking, Magnetic tracking or Inertial tracking. In this paper, a six-degrees-of-freedom (6-DoF) optical tracker (TrackIR™) was used to record the coordinates of the pilot's head motion in real time on the simulator bed. During the process of acquisition of the coordinates of head movement by optical tracker, the data may get missed due to stray light interference or any other kind of occlusion. To predict the missing data Self Healing Neural Model (SHNM) was applied. More than 88% of accuracy was achieved in prediction of three different sets of missing data. Results were also compared with Back Propagation Neural Network (BPNN).

Keywords: Head Tracking, Neural Network, Self healing, Recovery, Avionics

Introduction

Head Tracking being a pivotal part of HMD is the process of synchronizing the coordinates of the environmental scene (both with and without moving objects) in real time. Various techniques can be utilized for pose estimation of the head such as electromagnetic tracking, inertial tracking, optical tracking, mechanical tracking, etc. Optical trackers have comparatively higher accuracy and their feature of being wireless in nature allows the user to work in the large volume of space. The data acquired by the head trackers[1] generally consists of six-degrees-of-freedom (6-DoF) coordinates. The 6-DoF data acquired in all the techniques is a combination of position (Coordinates of X-axis, Y-axis, and Z-axis) and angular motion of head (Yaw angle, Pitch angle and Roll angle) as explained in the Table 1. Due to various reasons like sensor malfunctioning or stray light interference, the 6-DOF data acquired by the optical tracker may get corrupted or missed causing reduction in tracking accuracy. Artificial Neural Networks[2] can be applied to predict[3] the missing data. In this paper, we will discuss the prediction of missing data using Self healing neural model (SHNM)[4].

*Author for Correspondence
E-mail: smarajitg@hotmail.com

Proposed approach

The system setup for this work was comprised of cockpit simulator, TrackIR™ 5 optical tracker[5,6] operating with Field of View (FoV) of 51.7° at 120fps sampling rate with response time of 9 ms. The interface of the optical tracker was USB 2.0. The physical dimensions of the tracker were 1.5 in (3.81 cm) L x 2 in (5.1 cm) W x 0.57 in (1.45 cm) H. Dell Inspiron 15 5000 series was used for data acquisition operating under Microsoft Windows 10. TrackIR™ 5 optical tracker acts as a source to generate the Infrared (IR) light. The incoming IR light was reflected back by the three retro-reflective

Table 1 — Description of the movements of the head

DoF	Information
X	Forward and Backward translational coordinate of the pilot's head
Y	Left and right translational coordinate of the pilot's head
Z	Up and Down translational coordinate of the pilot's head
Yaw	Rotational coordinate of the pilot's head along Z-axis
Pitch	Rotational coordinate of the pilot's head along Y-axis
Roll	Rotational coordinate of the pilot's head along X-axis

markers, which were assembled in the TrackClip which was placed on the helmet/head[7] of the pilot. The reflected IR light was detected by the infrared camera[8] present in TrackIR™ 5, which then tracked the positional and orientation coordinates of the head of the pilot[9].

Experimental setup

The system was easy to set up and simple to use, but it was capable of performing all the complex calculations that provided both position and orientation data of the head of the pilot on the simulator bed. The experimental setup for the data acquisition through optical tracker is shown in Figure 1. The 6-DoF data of the head movements was then collected by varying the head in different directions and angles. The data acquired in this work had total 4400 instances. Each instance represented the particular position and orientation of the pilot's head. The available data of 4400 instances including missing data acted as an input for the SHNM.

The available data set was then checked for the number of missing instances present. The missing instances were denoted by "0*s*" and each "0" was corresponded as dummy neuron and its value was recovered by healing function S_H. Sample data of the whole dataset used in this work has been shown in Table 2. The occlusion or interference due to the stray light in the optical tracker could lead to some missing instances during data acquisition of pilot's head coordinates for a short duration. This could degrade the performance of HMD. To eliminate this problem, the data which could not be recorded at the instant when the optical tracker malfunctioned due to an occlusion or stray light interference was recovered using SHNM. For the experimental purpose, the missing data set was constructed by including the deliberate occlusion or inclusion of the stray light in front of optical tracker for a particular instant of time. The recovery process of missing data was assured by the each iteration carried out by SHNM to recover the each instance of missing data. After recovery, the recovered data was analyzed for correctness and validation using supervised learning. In the final step, the accuracy of the recovered data against the actual data was computed. The threshold for the proposed system to compute the accuracy was assumed on the basis of average of self-healing cost over the available data set[4]. As it was observed through simulations that threshold range from 0.5 to 1 yielded the best results, hence 0.8 threshold value was used to compute the accuracy. The simulations through SHNM was done in MATLAB R2016a. The proposed system along with the workflow is described in the Figure 2.

Fig.1 — Experimental Setup of Optical Tracking System with software interface

Table 2 — Sample Data set

X	Y	Z	Yaw	Pitch	Roll
6.4	6.5	3.15	-14.4	23.5	-2.9
6.3	5.7	3.48	-14.3	16.6	-2.6
6.4	5.8	3.47	-14.6	17	-2.6
6.2	3.8	5.08	-14.7	5.9	-0.3
6	3	5.39	-14.5	5.2	-0.1
5.8	2.6	5.68	-13.9	4.8	-0.1
5.9	2.7	5.86	-13.4	4.9	-0.2
5.7	2.9	6.04	-13.1	5.3	-0.4
5.5	3	6.19	-13.3	5.4	-0.5
5.4	2.4	6.47	-13	3.9	-0.4

Background of self healing neural model

Self healing neural model was proposed by Sharma *et al.* in which they recovered the failed UAVs in a network environment[4]. This method provided the stabilized state with high accuracy and lesser errors during recovery in case of network failures among the UAVs. The proposed methodology applied in this paper provides the possibility to validate the recovery of missing values in an optical head tracking system. It provides the facility of using "Dummy Neurons" for the missing values whereas the other neural models[3] do not explicitly deal with recovery of missing values. A cost of healing function S_H is used which is given by the equation[4]

$$S_H\left(\sum_{i=1}^{k} e^{\sqrt{\frac{1}{S_T}\sum_i^{S^T}(W_j-W_a)^2}} + \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(E_j\right)^2}\right) \quad \dots (1)$$

where k is the total number of instances in the data set, S_T is the size of the whole data set, W is denoted as weight of the neural network, W_a is the average weight, N is total available correct instances in the

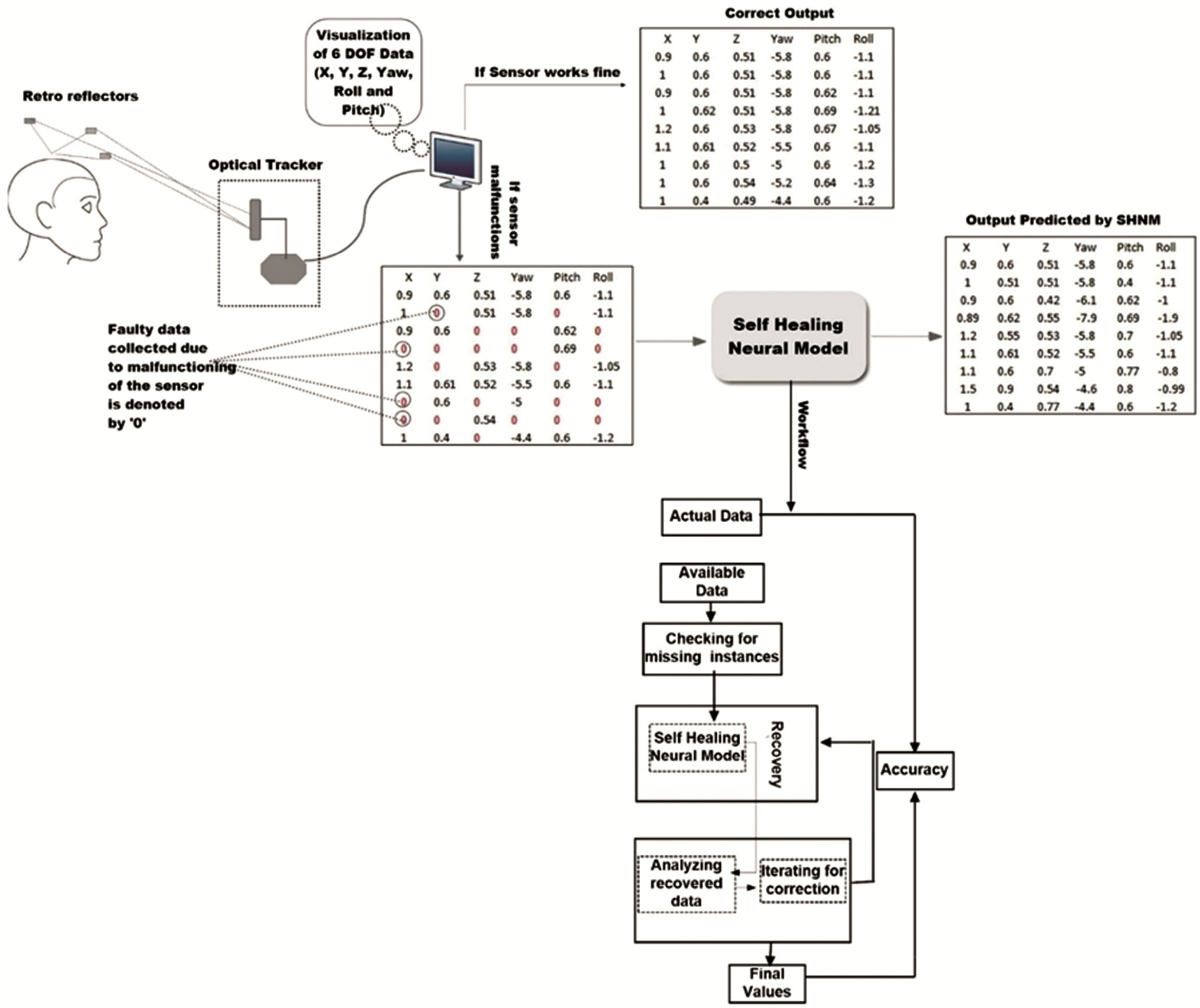

Fig.2 — Experimental description of optical head tracking along with workflow of the SHNM process for missing data prediction

data set, E is the number of missing instances in the data set and, i and j are the number of iterations in the experiment. The missing data was denoted by dummy neurons which was further predicted by the healing function (1). Time constraint was eliminated from the equation applied in the proposed system (1) unlike used in SHNM. The working of internal model of SHNM and further explanation can be obtained from[4].

Results and Discussions

In this section, the performance analysis of the proposed approach is discussed. To simulate the conditions of missing data in MATLAB R2016a, three sets of different missing percentage (10%, 25% and 35%) were created. The results obtained in this paper were better than the other neural networks[10, 11] like BPNN model, training of which involves three stages a) Feed for ward of the input training pattern b) Back propagation of the error generated c) Adjustment of the weights. The comparative results are shown in Table 3. Performance comparison of SHNM and BPNN neural model in prediction of missing 6-DoF data is presented in Figure 3 (a) and (b). The figures shown in this paper is the representation of predicted data from the missing data set with 35% of missing instances. SHNM predicted the missing data of X, Y and Z coordinates with 94.68%, 89.75% and 90.91% accuracy respectively which was more than the BPNN model for data set with 35% of missing instances. Accuracy of 95.90%, 95.30% and 91.11% was obtained by SHNM in Yaw, Pitch and Roll

Table 3 — Comparison of accuracy of SHNM with BPNN with different sets of missing data

Parameters	Accuracy of data against the missing percentage					
Missing percentage	10%		25%		35%	
	SHNM	BPNN	SHNM	BPNN	SHNM	BPNN
X	96.14%	91.05%	95.12%	90.20%	94.68%	89.69%
Y	92.50%	87.70%	91.34%	86.57%	89.75%	84.72%
Z	92.80%	87.30%	91.30%	86.10%	90.91%	85.63%
Yaw	97.10%	92.44%	96.21%	91.70%	95.90%	90.53%
Pitch	97%	91.90%	95.87%	89.9%	95.30%	89.20%
Roll	93.50%	84.60%	92.45%	83%	91.11%	82.81%

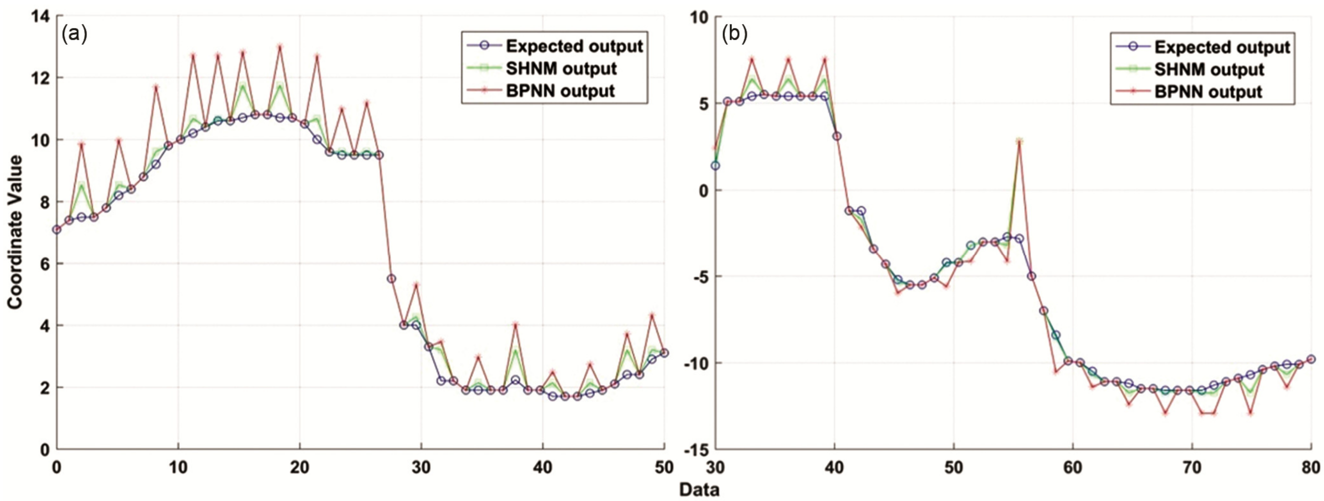

Fig.3 — Performance comparison of SHNM and BPNN neural model in prediction of missing 6-DoF data (a) Translational coordinate (b) Orientation angle Yaw

respectively, which was better than the BPNN model. The correctness of the proposed system was validated through supervised learning as the each outcome of all three missing data sets recovered through SHNM was compared with the actual true data set for the computation of the accuracy.

Conclusion

In an optical tracking, normally due to the occlusion or stray light interference the missing data can occur which can lead to the inaccurate acquisition of coordinates of the head. Due to which the performance of the HMD will get affected as, the information seen by the pilot in HMD will not be synchronized with external environment. To eliminate this problem, a system was proposed in which SHNM was used to predict the missing data. The number of instances of the head motion recorded in this paper were 4400. Three different sets 10%, 25% and 35% of missing data at a threshold value of 0.8 were used to obtain the simulated results. It was found that the accuracy of the recovered data from all the three missing data sets was more than 88%. The proposed approach can also help in designing low-cost flight simulator using optical tracking. The results obtained by SHNM were also compared with benchmark back propagation neural network and it was found that there was an increment of accuracy in SHNM by approximately 6%.

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