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ORIGINAL ARTICLE

Volodymyr V. Kindratenko · William R. Sherman

Neural network-based calibration of electromagnetic tracking systems

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Abstract Electromagnetic tracking systems are a common component of many virtual reality installations. Their accuracy, however, suffers from the distortions of the electromagnetic field used in calculating the tracker sensor's position. We have developed a tracker calibration technique based on a neural network that effectively compensates for the errors in both tracked location and orientation. This case study discusses our implementation of the calibration algorithm and compares the results with traditional calibration methods.

Keywords Tracker calibration · Electromagnetic tracker · Neural network · Virtual reality

1 Introduction

The definition of virtual reality requires that the computational system tracks the users in order to replace or augment one or more of their sensory inputs in accordance with their movement. Many developers of virtual reality systems have found that electromagnetic tracking systems (Raab et al. 1979) are a reasonable solution for implementing this essential part of the medium.

The popularity of electromagnetic tracking in VR systems stems from the many benefits provided by this technology. Unlike position tracking systems based on sonic and visual means of sensing movement, electromagnetic tracking systems are not limited by the line-of-sight. This allows the tracker transmitter to be hidden from the user, perhaps on the opposite side of large screens, and it allows many people to stand in close proximity without affecting the ability to track. Electromagnetic tracking also avoids problems due to inertia or requirements caused by physical connections between the tracked object and the tracking system as are the case with mechanical linkage-based tracking systems (Meyer et al. 1992). The sensors that accompany electromagnetic tracking systems are fairly easy to utilize, are relatively small and can be easily mounted on the body or objects to be tracked. Interfacing with several sensors associated with a single system is straightforward too.

Electromagnetic tracking systems, however, do have some serious deficiencies. In particular, tracking accuracy falls off rapidly with very limited overall range—typically within about 8 ft. Nixon et al. (1998) found that tracking error increases at a rate proportional to the fourth power of the distance between the transmitter and receiver units. Another major problem is that any magnetically active material in the vicinity can cause the tracked results to be warped (Nixon et al. 1998). This problem, however, can often be corrected via an analytical procedure referred to as *tracker calibration*.

Raab et al. (1979) foresaw the need for calibration and suggested that the correction of the distorted measurements can take the form of additive vectors for location error correction and a sequence of rotations for orientation error correction and can be stored either in a look-up table or as polynomials in the position space. Most of the work undertaken after Raab's report implements a variation of one of these two approaches. We have sought to apply and evaluate a neural network-based approach as an alternative to the way most electromagnetic tracking calibration has thus far been implemented.

2 Related work

A detailed survey of various tracker calibration techniques can be found in Kindratenko (2000); here we only briefly describe some of them.

Ghazisaedy et al. (1995) and Czernusenko et al. (1998) applied tri-linear interpolation to compensate for the errors in tracked location. Livingston and State (1997) used tri-linear interpolation for correcting the errors in the tracked location and a sequence of spherical linear interpolations between the quaternions repre-

V. V. Kindratenko (✉) · W. R. Sherman
National Center for Supercomputing Applications (NCSA), University of Illinois at Urbana-Champaign (UIUC), 405 N. Mathews Avenue, Urbana, IL 61801, USA
E-mail: kindr@ncsa.uiuc.edu
Tel.: +1-217-2650209
Fax: +1-217-2442909

senting the tracked orientation to correct the errors in the orientation.

Bryson (1992) used a weighted look-up table method to compensate the errors in the tracked location. Kindratenko and Bennett (2000) extended this technique to compensate the errors in both the tracked location and orientation. Briggs (1999) used a look-up table interpolation scheme to correct the errors in the tracked location similar to the one described in Livingston and State (1997). The difference between Briggs's and Livingston's methods is in the way the look-up tables are re-sampled from the measurements taken on an irregular grid.

Several researchers have used high-order polynomial fit. Bryson (1992) applied fourth-order polynomials to compensate for the errors in the tracker's location. Kindratenko (1999) and Ikits et al. (2001) extended this technique to correct the errors in the tracker orientation as well. Kindratenko (1999) used Euler angles, whereas Ikits et al. (2001) used quaternionial representation for orientation.

Zachmann (1997) proposed a scattered data interpolation scheme using Hardy's Multi-Quadric method with LU matrix decomposition to solve the interpolation equations. The rationale for using this approach is that Hardy's Multi-Quadric polynomials oscillate less than Newton or Lagrange interpolation polynomials.

It is usually assumed that the error in tracked location and orientation is a function of the tracker location only. Livingston and State (Livingston and State 1997) suggested that the tracker orientation plays a role as well; however, we have not seen any other reports in the literature researching this conclusion. Moreover, Ikits et al. (2001) pointed out that the rotation error definition used in Livingston and State (1997) is orientation dependent, which may explain the rotation error dependence on the orientation observed by the researchers. Therefore, in thus study, we assume that the error in tracked location and orientation is the function of the tracked location only.

Thus far, most of the calibration techniques reported in the literature are based either on an interpolation scheme (tri-linear or look-up table) or on a polynomial fit (high-order polynomials or Hardy's Multi-Quadric polynomials). Both approaches require a relatively dense calibration table, otherwise they may not provide the desirable accuracy. The polynomials are quite good at capturing the overall shape of the distorted field; however, they miss smaller details, e.g., when sudden but small localized changes to the electromagnetic field occur. The lower the order of the fitting polynomial, the greater the error. However, as the order increases, the polynomial oscillations occur. This results in additional errors, particularly at the locations where the errors were initially low (Kindratenko 1999).

Interpolation-based calibration techniques attempt to linearly interpolate the error value at each location based on the error values of nearby locations. However, the actual errors change nonlinearly. As a result, interpolation techniques perform well in the presence of small error changes and perform relatively poor when the electromagnetic field warps substantially.

3 Proposed method

We propose to use a feed-forward neural network (Bishop 1995; Müller et al. 1995) to approximate the shape of the distorted electromagnetic field, and thus, to predict the receiver's actual position (both location and orientation) from its reported position. The entire calibration procedure consists of obtaining an appropriate training set (calibration table) and training the network until the overall network output error reaches a desirable level of accuracy. Once the network is trained, it can be used to correct the tracker errors.

3.1 Calibration table measurements

The main use of the calibration table is to establish a correspondence between the true position and the position reported by the tracking system. In practice, this requires an alternative location sensing tool and usually can be achieved only at some limited number of locations. As we move the tracker sensor, the electromagnetic tracking system reports tracker sensor position relative to the origin of the tracker transmitter. Our goal therefore is to measure the actual physical position of the tracker sensor relative to the origin of the tracker transmitter. Several techniques have been proposed in the literature; we use the calibration table measurement technique described in Kindratenko (1999) and Kindratenko and Bennett (2000). The procedure consists of moving the receiver on a regularly spaced grid with known coordinates and with a known constant orientation and recording both the known true position of the tracker sensor and the position reported by the tracking system. The resulting table contains tracker readings that are taken on the regular grid in the undistorted true space.

It is important to avoid any further magnetic field distortions while measuring the exact location of the sensor with the help of an alternative measuring technique. To achieve this, a simple sensor holder was built consisting of a 1×1×0.1 foot wooden platform with a housing attached at the top and a set of plastic pipes of the length 2, 3, 4, 5, 6, and 7 ft that can be plugged into the housing (Fig. 1a). Moving the platform on the regular grid marked on the floor (Fig. 1b) and changing the pipes allows the placement of the sensor at the points whose locations can be precisely determined. After a very careful alignment, the precision of this measuring technique is ± 0.01 m, $\pm 1°$.

The main advantage of this approach is its simplicity and a very low cost. However, this is a time-consuming technique and it requires a special care to ensure the desirable degree of accuracy. Also, the relation (trans-

Fig. 1 Calibration table acquisition device used in this study. Two-dimensional grid (**b**) is laid on the floor in front of the I-Desk; sensor holder (**a**) is moved on the grid

formation from one system to another) between the grid-based coordinate system and the electromagnetic tracker coordinate system needs to be known.

The data measurement procedure is repeated twice, once on the grid and once in-between the grid, resulting in two different datasets. The first dataset (calibration table) is used to train the network whereas the second dataset (validation table) is used to verify the quality of the calibration once the network is trained.

3.2 Neural network design considerations

Our goal is to devise a neural network capable of predicting the true tracker sensor position based on its tracked position. It has been shown that a feed-forward neural network with hidden layers can represent any smooth continuous function $R^n \rightarrow R^m$ (Bishop 1995; Müller et al. 1995). This is achieved by training the neural network with an error back-propagation algorithm by presenting examples of known function values for known function arguments (the calibration table). In our case, we assume that the error in the tracked location and orientation is the function of the tracked location only. Therefore, the neural network designed for location error correction should accept three inputs—x, y and z coordinates of the tracked location—and should produce three outputs: x, y and z coordinates of the corrected location. In this study, we use Euler angles to represent the tracker orientation. Therefore, in order to compensate for the errors in the tracked orientation, the neural network should accept three inputs—x, y and z coordinates of the tracked location—and should produce three outputs: rotation error for yaw, pitch and roll. These rotation errors are then used to rotate the actual tracked rotation to compensate for the field distortion as described in Kindratenko (1999).

Thus, we need to implement two separate neural networks. The first neural network is used to directly predict the true location based on the tracked location, and the second neural network is used to predict rotation errors for a given tracked location. We do not attempt to merge these two networks into one because the functions that they represent behave quite differently and are defined on different domains. We also do not attempt to directly predict the corrected Euler angles because we would need to supply the network with both the tracked location and orientation, which is a mixed domain data.

We still need to decide on the network architecture (number of hidden layers, number of neurons in each layer, type of transfer functions, etc.) and on the type and parameters of the error back-propagation training algorithm. There is no precise recipe about selecting the right network complexity for a given problem and the optimal solution can often be found only experimentally. The number of hidden layers and number of neurons in each layer is related to the complexity of the function to be represented by the network. The larger the number of local minima and maxima in the function, the more likely it will require a network with higher complexity. However, higher complexity may also lead to a network which is not able to generalize well enough and/or will require a lengthy training procedure.

In this study, we use a *single hidden-layer network* architecture with tan-sigmoid transfer functions for the neurons in the hidden layer and linear transfer functions for the neurons in the output layer (Bishop 1995; Müller et al. 1995). The exact number of hidden-layer neurons required for an optimal solution is determined experimentally by training networks of different sizes and identifying the one with the best overall performance.

Various error back-propagation training algorithms can be employed to train a feed-forward neural network (Bishop 1995; Müller et al. 1995). Ideally, we would like the training procedure to be fast (the network should converge in a small number of iterations), and we would like to have an obvious training termination criterion. We evaluated several such techniques and selected *Bayesian regularization in combination with Levenberg-Marquardt training* (Foresee and Hagan 1997). Bayesian regularization minimizes a linear combination of squared errors and weights. It also modifies the linear combination, so that at the end of training the resulting network has good generalization abilities.

The neural network architecture and training procedure used in this study were selected after evaluating a number of other network configurations. For example, we considered a multilayer neural network with the standard back-propagation training, but were not able to achieve a desirable degree of performance (Saleh et al. 2000). This points out the main difficulty when using a neural network-based approach: there is no precise recipe about the network architecture and training procedure. One should consider several alternatives before settling down with a particular technique.

4 Experimental results and discussion

The proposed calibration technique was tested with three tracking systems: Ascension Technology Flock of Birds installed in a CAVE^{TM}-like environment (referred to as *FoB1*), Ascension Technology SpacePad used with an ImmersaDesk^{TM} (*SpacePad*) and Ascension Technology Flock of Birds installed in the CAVE (*FoB2*). The size of the tracked volume and the number of measurements used in the calibration and validation tables are given in Table 1. Errors in tracked location and orientation are given in Table 2. Note that FoB2 dataset is very sparse; the measurements for the calibration table were taken 2 ft apart. Therefore, we expect that look-up table interpolation calibration technique should perform poorly as compared, for example, to the high-order polynomial fit calibration technique.

Our first task is to find the optimal number of neurons in the hidden layer for each dataset. The approach that we have chosen consists of training neural networks with 3 to 21 neurons in the hidden layer using data from

Table 1 Dimensions of the calibration and validation datasets

Dimensions	Tracking system								
	FoB1			SpacePad			FoB2		
	Minimum (m)	Maximum (m)	Step (m)	Minimum (m)	Maximum (m)	Step (m)	Minimum (m)	Maximum (m)	Step (m)
	Calibration table								
x	−1.24	1.24	0.31	−0.93	0.93	0.31	−1.24	1.24	0.62
y	0.62	1.86	0.31	0.62	1.55	0.31	0.62	2.48	0.62
z	−0.93	1.24	0.31	0.16	1.40	0.31	−1.24	1.24	0.62
#	432			140			88		
	Validation table								
x	−1.09	1.09	0.31	−0.78	0.78	0.31	−1.09	1.09	0.31
y	0.62	1.86	0.31	0.62	1.55	0.31	1.52	1.52	N/A
z	−0.78	1.09	0.31	0.31	1.24	0.31	−1.09	1.09	0.31
#	336			72			64		

The origin of FoB1 coordinate system is in the middle of the CAVE; the origins of SpacePad and FoB2 coordinate systems are in the middle of the floor of the I-Desk/CAVE

Table 2 Error statistics for uncalibrated tracking systems

Statistics	Tracking system					
	FoB1		SpacePad		FoB2	
	Location (m)	Orientation (°)	Location (m)	Orientation (°)	Location (m)	Orientation (°)
Mean	0.161	8.8	0.165	5.5	0.128	3.6
SD	0.111	5.8	0.067	3.5	0.099	1.6
Minimum	0.022	0.0	0.016	0.4	0.024	1.0
Maximum	0.619	27.8	0.307	18.0	0.476	7.9

Errors in the tracked location are measured as the distance between the tracked location and the actual true location of the tracker sensor. Errors in the tracked orientation are measured as the angle between the direction of the tracked orientation and the actual true orientation of the tracker sensor

the calibration datasets and validating their performance using data from the validation datasets. Once a particular network is trained, we present the corresponding validation dataset to the network and compute the network's output, which is then used to compute the average error between the expected true position stored in the validation file and the calibrated position. The results are shown in Figs. 2 and 3. On the basis of these results, we select the most appropriate number of hidden-layer neurons for a given dataset and a given calibration domain (location and orientation). Thus, in essence, we calibrate the tracking system with different networks and pick up the one that produces the best results. As seen from the plots, an optimal solution for each dataset in each calibration domain typically requires a different number of neurons. For example, FoB2 dataset requires the network with 11 neurons in the hidden layer in order to produce the best location calibration results and requires the network with 12 neurons in order to produce the best orientation calibration results. Table 3 summarizes our final findings for all three datasets.

Once we know which network performs best, we can use it to calibrate the system. Table 4 summarizes the results of the calibration based on the data from the validation tables. For example, the average tracked location error for FoB1 validation dataset is 0.161 ± 0.111 m (Table 2), whereas the average location error after the calibration is 0.025 ± 0.01 m (Table 4)—almost an order of magnitude improvement. Likewise, the average tracked orientation error for FoB1 dataset is $8.8 \pm 5.8°$ (Table 2), whereas the average orientation error after the calibration is $1.9 \pm 1.3°$ (Table 4)—a fourfold improvement over the uncali-

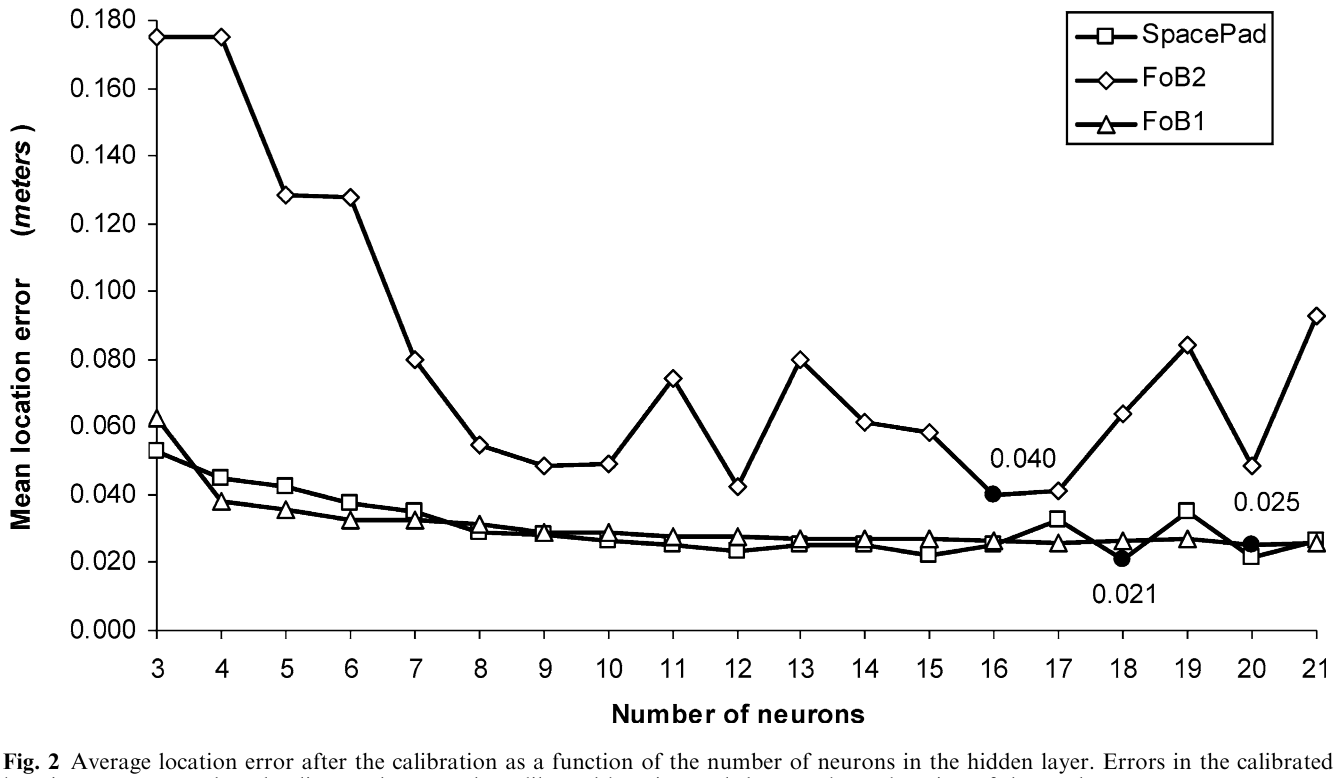

Fig. 2 Average location error after the calibration as a function of the number of neurons in the hidden layer. Errors in the calibrated location are measured as the distance between the calibrated location and the actual true location of the tracker sensor

Table 3 Summary of the neural network training and optimal number of neurons in the hidden-layer selection procedures for all three datasets

Dataset	Calibration domain	Calibration error	Number of neurons	Number of epochs
FoB1	Location	0.025 m	20	519
	Orientation	1.9°	11	247
SpacePad	Location	0.021 m	18	531
	Orientation	2.4°	10	996
FoB2	Location	0.040 m	16	160
	Orientation	1.6°	12	237

Table 4 Error statistics for the calibrated tracking systems

Statistics	Tracking system					
	FoB1		SpacePad		FoB2	
	Location (m)	Orientation (°)	Location (m)	Orientation (°)	Location (m)	Orientation (°)
Mean	0.025	1.9	0.021	2.4	0.040	1.6
SD	0.010	1.3	0.014	2.0	0.023	1.1
Minimum	0.005	0.1	0.003	0.1	0.006	0.2
Maximum	0.055	7.0	0.078	9.3	0.116	6.0

Errors in the calibrated location are measured as the distance between the calibrated location and the actual true location of the tracker sensor. Errors in the calibrated orientation are measured as the angle between the direction of the calibrated orientation and the actual true orientation of the tracker sensor

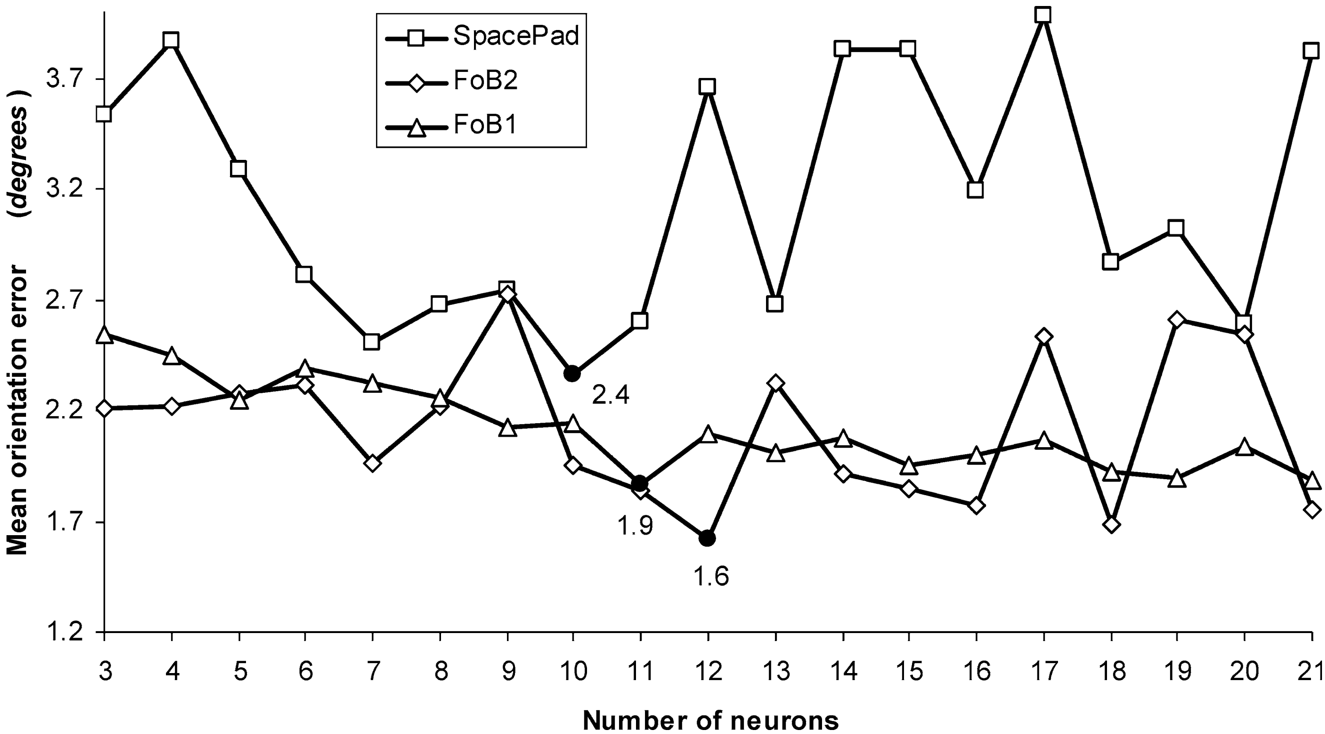

Fig. 3 Average orientation error after the calibration as a function of the number of neurons in the hidden layer. Errors in the calibrated orientation are measured as the angle between the direction of the calibrated orientation and the actual true orientation of the tracker sensor

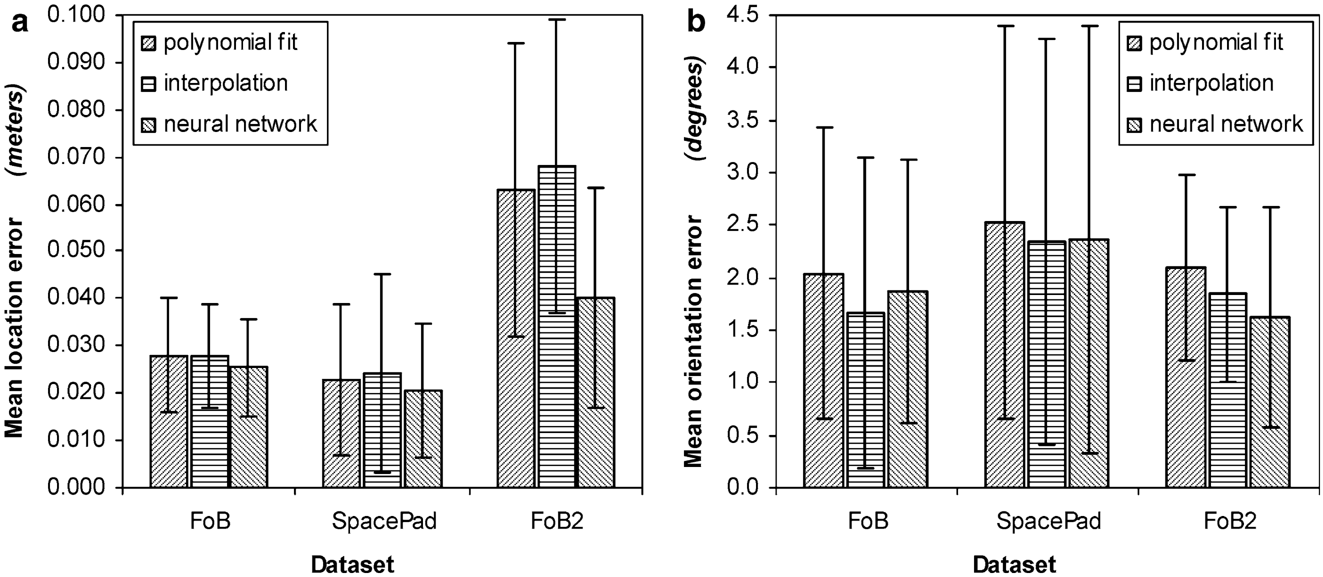

Fig. 4 Comparison of the results for location (**a**) and orientation (**b**) calibration by fourth-order polynomial fit, look-up table interpolation and the neural network-based calibration techniques. *Vertical bars* represent average error, whereas *error bars* indicate standard deviation about the average error (see Table 5 for numerical values)

Table 5 Calibrated location and orientation errors after the calibration with three different calibration techniques

		Location (m)			Orientation (°)		
		FoB1	SpacePad	FoB2	FoB1	SpacePad	FoB2
Polynomial fit	Mean ± SD	0.028 ± 0.012	0.023 ± 0.016	0.063 ± 0.031	2.0 ± 1.4	2.5 ± 1.9	2.1 ± 0.9
	Minimum, maximum	0.001, 0.070	0.007, 0.088	0.013, 0.140	0.0, 7.8	0.4, 9.0	0.2, 4.3
Interpolation	Mean ± SD	0.028 ± 0.011	0.024 ± 0.021	0.068 ± 0.031	1.7 ± 1.5	2.3 ± 1.9	1.9 ± 0.8
	Minimum, maximum	0.005, 0.081	0.004, 0.122	0.020, 0.151	0.0, 6.8	0.3, 9.2	0.4, 4.5
Neural network	Mean ± SD	0.025 ± 0.010	0.021 ± 0.014	0.040 ± 0.023	1.9 ± 1.3	2.4 ± 2.0	1.6 ± 1.1
	Minimum, maximum	0.005, 0.055	0.003, 0.078	0.006, 0.116	0.1, 7.0	0.1, 9.3	0.2, 6.0

Table 6 *t* test results

Domain	*t* test samples	*t* test value		
		BoF1	SpacePad	FoB2
Location	Polynomial fit—neural network	5.82	2.26	4.68
	Interpolation—neural network	6.29	1.54	5.26
Orientation	Polynomial fit—neural network	4.66	1.53	2.59
	Interpolation—neural network	−3.63	−0.18	1.45
	t-critical for $\alpha = 0.05$ and the given degree of freedom	1.97	1.99	2.00

When the *t* test value is closer to 0 than the *t* critical value, the initial hypothesis that there is no statistical difference between the calibration results obtained with two different calibration procedures is true. The results indicate that in most cases no statistically significant improvements were obtained by the neural network-based calibration technique as compared to other calibration techniques when attempting to calibrate the SpacePad electromagnetic tracking system. At the same time, the improvements obtained for two other electromagnetic tracking systems when using neural network-based calibration technique are, in most cases, statistically significant

brated orientation. Similar results were obtained for two other tracking systems. Thus, in all cases the neural network-based calibration technique was able to significantly decrease errors in both the tracked location and the tracked orientation.

Our second task is to analyze the performance of the neural network-based calibration as compared to other calibration techniques found in the literature. In particular, we are interested in the overall performance and its statistical (in)significance. The overall performance can be measured using first- and second-order statistics (mean, standard deviation, etc.) about the difference between the true tracker sensor position and the position obtained as the result of calibration using different calibration techniques. The statistical significance of the differences in performance can be verified with paired two sample t test ("Student" 1908). In our case, this test is used to determine whether the calibration results obtained with two different calibration techniques are likely to have distributions with equal average values, or, in other words, there is no statistically significant difference between the results obtained with different calibration techniques. When the t test value is closer to 0 than the t critical value for the corresponding degrees of freedom at 95% confidence level, the initial hypothesis that there is no statistical difference between the calibration results obtained with two different calibration procedures is true.

We compare the calibration improvements obtained with the proposed method with the improvements obtained with the fourth-order polynomial fit calibration technique (Kindratenko 1999) and the interpolation-based calibration scheme (Kindratenko and Bennett 2000) based on the same calibration and validation datasets used in this study. The results are shown in Fig. 4 and Table 5. On the basis of the comparison of the mean errors, the neural network calibration technique outperformed two other calibration techniques when applied to correct tracked locations. However, we obtained mixed results while attempting to correct the errors in the tracked orientation: the interpolation-based method outperformed the neural network-based technique in two out of three cases. It is interesting to note that the neural network-based approach outperformed two other techniques both in location and orientation calibration when applied to FoB2 dataset, which is a sparse dataset as compared to two other datasets. This indicates that the neural network-based calibration approach may require a smaller calibration dataset.

Most of the improvements on FoB1 and FoB2 datasets achieved when using the neural network-based calibration technique compared to other calibration methods are statistically significant as verified with paired two sample Student's t test (Table 6). The improvements for SpacePad dataset in most cases are not statistically significant. However, the practical significance of the improved calibration results depends on the application in which the tracker system is used. For example, in an architectural walk-through application, the difference between 0.063 and 0.04 m (calibrated FoB2 dataset) is negligible. However, the same error may be very significant in a medical application in which medical devices are tracked and remotely controlled. Therefore, the importance of the improvements obtained with the neural network calibration technique should be judged in the context of the actual application for which the calibration is being performed.

5 Conclusions

In this study, we applied a single-layer feed-forward neural network to calibrate the location and orientation errors typically present in electromagnetic tracking devices. We evaluated the proposed technique with three different tracking systems and found that it can be used to significantly improve their tracking accuracy. We also found that this method produces results that are often better than the results produced by two other well-known techniques. In particular, we were able to achieve lower overall errors while calibrating tracked location. However, look-up table rotation interpolation outperformed the neural network location calibration technique in two out of three cases. We also found some indications that the neural network-based calibration approach may require a smaller calibration table, although a more detailed study is required to verify this observation. Even though the improvements obtained with the proposed calibration technique can be statistically significant, the benefits of this approach should be considered within the framework of the actual application for which the calibration is thought to be applied.

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References

Meyer K, Applewhite H, Biocca F (1992) A survey of position trackers. Presence 1(2):173–200

Nixon M, McCallum B, Fright W, Price N (1998) The effects of metals and interfering fields on electromagnetic trackers. Presence 7(2):204–218

Raab F, Blood E, Steioner T, Jones H (1979) Magnetic position and orientation tracking system. IEEE Trans Aerospace Electron Syst 15(5):709–718

Bishop CM (1995) Neural networks for pattern recognition. Oxford University Press, New York

Bryson S (1992) Measurement and calibration of static distortion of position data from 3D trackers. In: Proceedings of SPIE conference on stereoscopic displays and applications III, San Jose, CA, pp 244–255

Ghazisaedy M, Adamczyk D, Sandin D, Kenyon, DeFanti T (1995) Ultrasonic calibration of a magnetic tracker in a virtual reality space. In: Proceedings of the IEEE virtual reality annual international symposium (VRAIS '95), Research Triangle Park, NC, pp 179–188

Czernuszenko M, Sandin D, DeFanti T (1998) Line of sight method for tracker calibration in projection-based VR systems. In: Proceedings of 2nd international immersive projection technology workshop, Ames, Iowa, pp 11–12, CD-ROM

Livingston M, State A (1997) Magnetic tracker calibration for improved augmented reality registration. Presence 6(5):532–546

Zachmann G (1997) Distortion correction of magnetic fields for position tracking. In: Proceedings of computer graphics international (CGI'97), Hasselt, Belgium, pp 23–27

Briggs W (1999) Magnetic calibration by tetrahedral interpolation. In: Proceedings of NIST-ASME industrial virtual reality symposium, Chicago, IL, November 1999, MH-Vol. 5/MED-Vol. 9:27–32

Kindratenko V (1999) Calibration of electromagnetic tracking devices. Virtual Reality Res Dev Appl 4:139–150

Ikits M, Brederson JD, Hansen C, Hollerbach J (2001) An improved calibration framework for electromagnetic tracking devices. IEEE Virtual Reality

Kindratenko V, Bennett A (2000) Evaluation of rotation correction techniques for electromagnetic position tracking systems. In: Proceedings of the virtual environments 2000 eurographics workshop, Amsterdam, The Netherlands, pp 13–22

Müller B, Reinhardt J, Strickland MT (1995) Neural Networks, an Introduction, 2nd edn. Springer, Berlin Heidelberg New York

Foresee FD, Hagan MT (1997) Gauss-Newton approximation to Bayesian regularization. In: Proceedings of the 1997 international joint conference on neural networks

Kindratenko V (2000) A survey of electromagnetic position tracker calibration techniques. Virtual Reality Res Dev Appl 5:169–182

Student (1908) On the probable error of the mean. Biometrika 6:1–25

Saleh T, Kindratenko V, Sherman W (2000) On using neural networks to calibrate electromagnetic tracking systems, NCSA Technical Report, December 7