Patient Positioning Using Artificial Intelligence Neural Networks, Trained Magnetic Field Sensors and Magnetic Implants

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The purpose of this study was to evaluate the precision of a sensor and to ascertain the maximum distance between the sensor and the magnet, in a magnetic positioning system for external beam radiotherapy using a trained artificial intelligence neural network for position determination. Magnetic positioning for radiotherapy, previously described by Lennernäs and Nilsson, is a functional technique, but it is time consuming. The sensors are large and the distance between the sensor and the magnetic implant is limited to short distances. This paper presents a new technique for positioning, using an artificial intelligence neural network, which was trained to position the magnetic implant with at least 0.5 mm resolution in X and Y dimensions. The possibility of using the system for determination in the Z dimension, that is the distance between the magnet and the sensor, was also investigated. After training, this system positioned the magnet with a mean error of maximum 0.15 mm in all dimensions and up to 13 mm from the sensor. Of 400 test positions, 8 determinations had an error larger than 0.5 mm, maximum 0.55 mm. A position was determined in approximately 0.01 s.

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It is important to position a patient accurately during a course of external beam radiotherapy in order to avoid insufficient dosage in the target volume or high doses in organs at risk (1). The principles for magnetic positioning using magnetic implants have already been presented by Lennernäs & Nilsson (2, 3) (Pat. Pend.). A common dilemma with high-precision fixation and positioning systems is that they tend to be complicated and unsuitable for standard external beam radiotherapy. However, they are often well adapted for special treatment modalities, such as boosting with high-precision proton or photon radiotherapy and stereotactic treatments (2–8).

Previously, the magnetic position system has had problems (3). The system is time consuming, the sensors are large and the distance between the sensor and the implant is too short. This is due in part to the mechanical structure of the sensor and also the large time-consuming multiplexing of the signals in the electronic components. Whereas the structural problems and multiplexing of signals are readily overcome, there is no obvious solution to the problem of the position calculation since the sensors are larger than the desirable resolution. The logical solution is to put the signals from all magnetic-field-sensitive units of the sensor into an algorithm for position determination. However, such an algorithm is not available, and the signals from the sensors could give rise to certain noise that could influence the calculation.

This study presents a promising method that is fast, needs no mechanical parts and makes it possible to increase the distance between the sensor and the magnetic implant. Instead of developing an algorithm for positioning, a neural network was trained for all possible positions of a magnet, in steps of 1.25 mm in front of the sensor. The result is a network that can rapidly and precisely position the magnet not only in the X and Y dimensions, but also in the Z dimension, that is the distance between the magnet and the sensor.

MATERIAL AND METHODS

The original positioning system consisted of three magnetic implants, three magnetic field sensors and a control unit with a monitor, multiplexer, A/D-converters and a high accuracy power supply (2). However, in this study only one sensor and one magnet were used for the neural network analysis (see Fig. 1). The system is discussed in detail in Lennernäs (3).

The magnetic implant, magnetic field sensor and control unit

The magnetic implant consists of a cylindrical 5 mm × 5 mm neodymium-iron-boron magnet (ELFA, Sweden). The

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magnet is mounted on a servomotor mechanism, which makes it possible to vary the distance between the magnet and the sensor from 0 to 8 mm in steps of 1 mm, enabling the determination of the Z dimension.

The sensors consist of 16 magnetic-field-sensitive units measuring 4.1 × 3.0 mm (SS49, Honeywell®), placed in four rows with four columns in an area measuring 20 mm × 20 mm. The output signal of the units is directly proportional to the magnetic field applied to the sensor. The sensor is mounted on a specially constructed high-precision XY-board, which has a range of 10 mm in both the X and Y directions. Movements in the up–down direction are called the Y dimension and the lateral movements are the X dimension.

The control unit is a computer with suitable interfaces. The signals from the 16 units in the sensor were collected and multiplexed to one single signal line, which was connected to the control unit. The computer read all signals from the units engaging one unit at a time.

Measurements

The previous system was designed to scan the area above each magnetic marker and to find the position with the strongest signal (3). However, this set-up uses the servomotor mechanisms to find all possible positions in steps of 1.25 mm in front of the sensor and in all dimensions (X, Y and Z). The middle of the sensor was the starting-point for the X and Y dimensions, and the magnet was positioned $\pm$ 5 mm from this point, a total of 9 steps. The Z dimension range was from 0 mm to 8 mm. The control unit created a file and stored 729 readings for later training of the neural network. A new file was then created with 100 random positions to test the training of the neural network. The positions in the random file were entirely random and continuous, that is, not divided into steps of 1.25 mm.

This procedure was repeated three times, creating a total number of three pairs of training and random test sets (Tests 1–3). A separate training session was performed to test the ability of the network to deal with distances ranging from 5 to 13 mm between the sensor and the magnet (Test 4). The relative positions of the magnet and the sensor were changed between the creation of the three pairs of training and random test files, but not between the creation of the training set and the corresponding random test set.

In order to show the relationships between the magnet and the output from the magnet-sensitive units, the voltage signals from four units of one row of the sensor were stored and presented. The distances between the units and the magnet were changed during this evaluation.

Neural networks, general information

Users do not necessarily need any knowledge of a neural network in order to be able to use it. It can be regarded as a black box with two modes, viz. learning and solving, and learning can be terminated at a certain error level. In an ordinary computer, the program solves a problem by processing instructions one by one. In a neural network, the whole problem is presented at once and the solving is the result of the signal flow through the network. Neural networks differ from other computer programs in that they are trained and not programmed to solve a problem. There are different types of neural networks, the most common being the back-propagation neural network.

In a neural network, the neurons are usually organized in layers, in an input, an output and a middle or hidden layer. The size of a layer is determined by the amount of data processed. All the neurons, often called nodes in a neural network, in one layer are connected only to the nodes in the adjacent layer. All learning or training in a neural network is achieved by modifying the connections between the nodes, i.e. the weights between the outputs and inputs. The learning procedure, that is the presentation of the input and the desired output, is repeated in order to reduce error to an acceptable level.

It is important to be aware of the fact that the training procedure must cover all possible areas of the data set of the solving procedure, but it must not cover all possible data. Instead, the network creates a model that is used for solving additional problems in the future. It is also important to have a reasonable amount of data and to use a reasonable number of training cycles. Learning is also dependent on two variables, namely the learning rate and the momentum. However, it is beyond the scope of this study to describe all the details in the use of neural networks.

Neural network in this study

The neural network used in this study is NeuroShell®2 (Ward Systems Group Inc., USA) (9). It is a back-propagation neural network with three layers; 16 input nodes

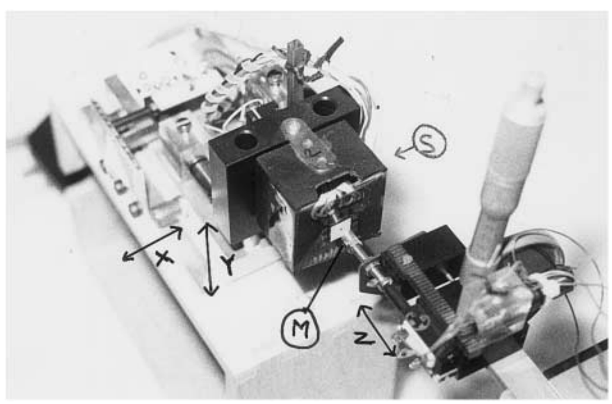

Fig. 1. The set-up of the system. The Magnet (M) is mounted on a microscope, making it possible to place the magnet in the middle of the sensor (S) before creation of the training and random test data set. The magnet can move in front of the sensor using three servomotors. The direction up and down is called Y and side to side X. These movements are carried out with the mechanism to the left in the Fig. The Z direction is the distance between the sensor and the magnet. This motion is carried out by the servomotor, to the right in the picture.

Table 1

Data for the random tests 1–4

	Test	Z	Y	X
R^2	1	0.999	0.997	0.992
	2	0.998	0.997	0.993
	3	0.991	0.997	0.992
	4	0.998	0.997	0.991
MSE	1	0.05	0.16	0.4
	2	0.07	0.13	0.38
	3	0.04	0.15	0.45
	4	0.52	0.15	0.48
MAE	1	0.05	0.1	0.15
	2	0.06	0.1	0.15
	3	0.05	0.1	0.15
	4	0.19	0.1	0.17
MAX	1	0.2	0.34	0.55
	2	0.33	0.28	0.5
	3	0.16	0.3	0.5
	4	0.47	0.33	0.55

If R^2 is 1, the training of the network is perfect and it will classify all positions in the random test sets (1–4) correctly in the dimensions X, Y and Z. MSE, Mean Squared Error, is determined as the mean of (actual value- predicted value)^2. Actual value is the actual position of the magnet and predicted value is the output from the trained neural network. MAE is the mean of all errors and MAX is the maximum error in one test. MSE, MAE and MAX are expressed in millimetres and R^2 is a relative quality parameter.

representing the magnetic-field-sensitive parts of the sensor, 34 hidden nodes and three outputs representing the three dimensions X, Y and Z. In this study, the training data files were used for the learning mode and the random data files were used for the solving mode. The learning rate was 0.6 and the momentum 0.9, and this remained unchanged during learning.

RESULTS

When all dimensions reached an error of less then 0.5 mm and no further decrease of the calculated error was noted, the training was stopped. Table 1 shows the results of all three training sessions of the neural network. Approximately 1430–2960 training cycles were needed in all three sessions to obtain an error of < 5 mm. One training session was carried out in 40–45 min. Mean absolute error is 0.05–0.15 mm and the mean-squared error is 0.05–0.052. The maximum error is < 0.55 mm in all sets of data in all dimensions (see Table 1 and Fig. 2). Note that these data had never, at any time, been presented to the neural network.

The output voltage of the magnetic-field-sensitive units of one row in the sensor is shown in Fig. 3. The signals and the magnetic field decreased significantly with an increase of the Z dimension. However, the neural network was able to determine positions in all dimensions up to 13 mm.

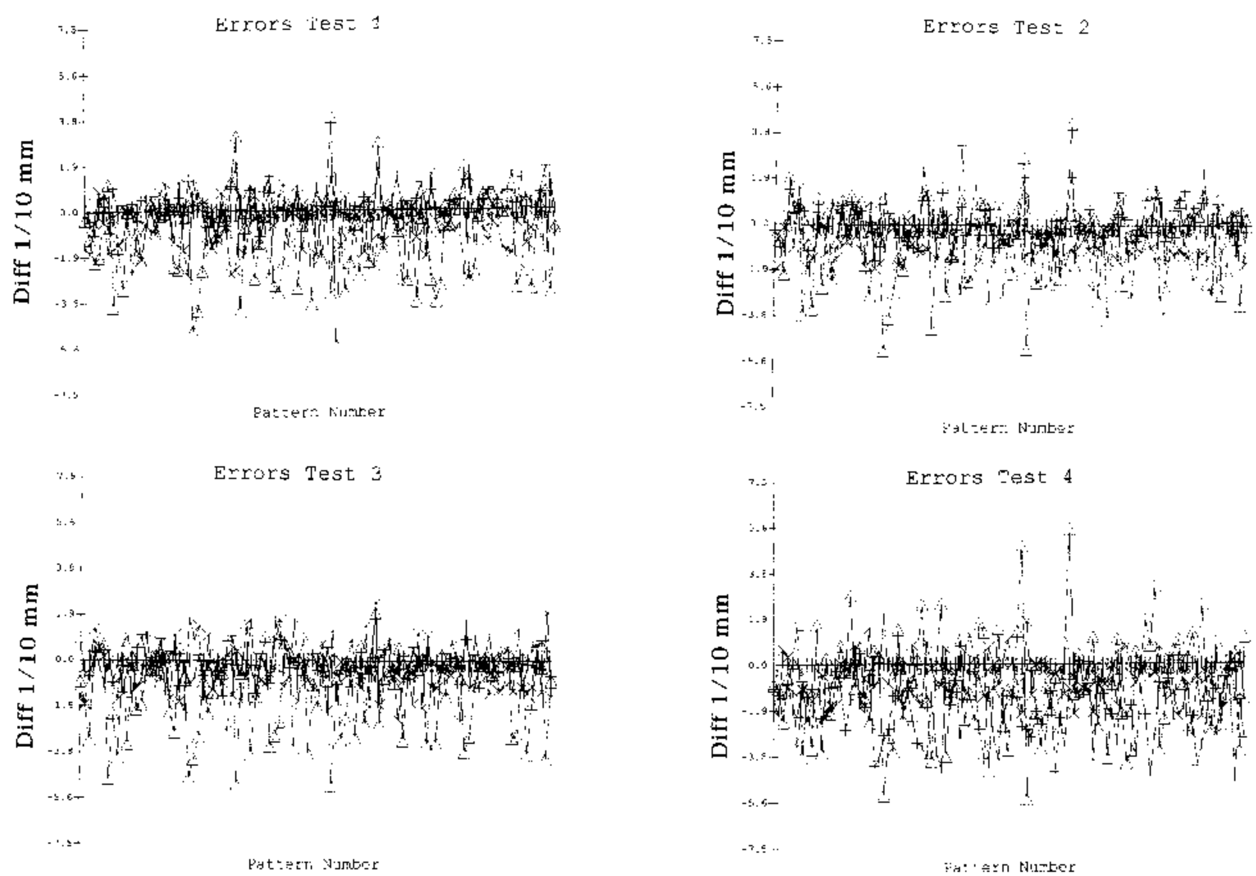

Fig. 2. The output of all errors of the 4 × 100 data of the test sets. Each marker represents an error. The Y-scale, Diff. is divided into 1/10 mm (1 = 0.1 mm). Error Test 4 includes the Z = 5–13 mm. All errors are between 0 and 0.55 mm.

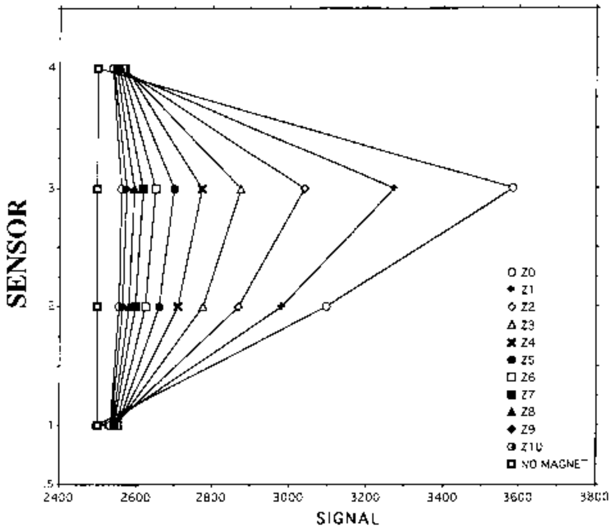

Fig. 3. The signal output (mV) for four units of one row of the sensor and the influence of the distance (1 mm–10 mm) between the sensor and the magnet in steps of 1 mm (Z0–Z10). The line NO MAGNET is the reading from the units without the magnet, that is the baseline readings from the units. The magnetic field produces an output of approximately 50mV at a distance of 10 mm.

DISCUSSION

In this article we present and evaluate a positioning technique based on artificial intelligence, in a positioning system based on magnetic implants and magnetic field sensors.

This active positioning system was able to detect and describe, in terms of direction, size and time, a displacement error before or during an external beam radiotherapy treatment. It also rectified the problems in the magnetic position system previously described, namely time consumption, limited distance between the sensor and the implant and large sensors, due in part to the mechanical structure of the sensor and also large multiplexing. Time for signal multiplexing could be reduced by using several or more rapid A/D converters, without external multiplexing electronics. Previously, it was thought that the position of the magnet could be determined by comparing the signals from several sensors in the sensor area. The sensor with the strongest signal would be the unit nearest the magnet and, by comparing the several signals, a position between the two sensors could be determined. However, this approach was not feasible, since no algorithm for position determination using this technique was available and it can be seen from this study that all inputs contribute significantly to the position determination. Instead, the sensors in the previously described system were mounted on an XY-board used for search and determination of the maximum point of the magnetic field; that is the position of the magnet.

The system in this study needs no mechanical parts, thus making it possible to increase the distance between the sensor and the magnetic implant and still decrease the time of position determination. Instead of developing an algorithm for positioning, a neural network was trained for all possible positions of a magnet in steps of 1.25 mm in front of the sensor and in steps of 1 mm between the magnet and the sensor. The Z dimension can be increased to at least 13 mm, but in a clinical working system it can be assumed that noise will influence this distance, since the signals from the units and the magnetic field decrease significantly with an increase in the Z dimension. However, the maximum distance is not known, as the capability for position determination was not increased to 13 mm from the sensor. In tests, noise has been introduced by adding up to 20 mV of 1–3 unit inputs without any influence on the output of the network. This is to some extent understandable, since all inputs contribute significantly to the position determination. It was not clear whether the five errors >5 mm were due to noise in the system or a real error in the training of the network.

Furthermore, attempts to use only the four most central units of the sensor failed, suggesting a relationship between the area of the sensor, the maximum resolution and Z distance of the system.

In conclusion, this new magnetic positioning system has a precision well suited for high-precision external beam radiotherapy. This system can be used for positioning throughout the whole radiotherapy chain, beginning with the dose-planning CT and diagnostic MRT at the simulator and ending with the last treatment on the accelerator. This study shows that the speed and accuracy of magnetic positioning can be improved by means of artificial intelligence.

A full-scale working system is under construction, which uses a high capacity A/D converter PC-card and DLL linked applications with Delphi® (Borland International, Inc., USA) and NeuroShell under Windows® 95/98 (Microsoft Corporation, USA). The aim is to develop a high-precision system for external beam radiotherapy with continuous position determination of the target.

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