Determination of Optimal CT Scan Parameters Using Radial Basis Function Neural Networks

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Abstract

X-ray computed tomography (CT) constitutes a promising technology for dimensional metrology, as workpieces can be measured in a non-destructive manner. Whereas CT has been used in the medical sector for decades, only recent advances in accuracy made its application for dimensional metrology possible. However, the accuracy of measurements greatly depends on the choice of scan parameters, which are usually set by a human CT operator. Several attempts have been made to reduce the operator’s influence on the measurement results. In this article, an approach to automatically choose the optimal parameters using radial basis function (RBF) neural networks is introduced. These networks can be trained with sample data to compute the optimal parameters for a given workpiece after being presented with selected properties of this workpiece.

Keywords: X-ray Computed Tomography, Artificial Neural Network, Radial Basis Function Network

1 Introduction

In recent years, X-ray computed tomography (CT) has increasingly been used as a method for dimensional metrology. Down to the present day, it is the only tool for evaluating the inner as well as the outer geometry of a workpiece non-destructively. This makes the technology indispensable for industrial applications. However, as opposed to medical applications, dimensional metrology puts high requirements on the accuracy of the measurement process. There are numerous machine parameters such as current, voltage, exposure time or type of filter that affect the quality of CT measured data in different ways and a closed formula for describing the influence of the various parameters on the measurement result has not been found yet. The machine parameters are usually set by a human operator, leading to subjective measurement results that depend on the experience of the user.

A lot of research has been done to objectively find the best machine parameters for different workpieces. In [1], the ideal parameters for two test specimens are determined by conducting a series of measurements on a CT system and evaluating several criteria to quantify the quality of the individual measurements and find the best parameters. A few researchers make use of a CT simulation software for finding the best parameters [2]. This approach often has the advantage of taking less time than scans on a CT, with the potential drawback of being less precise than measurements on a real CT system. A third approach is based on the idea, that the same set of parameters can be used for similar workpieces [3]. The authors use certain properties of a workpiece from which they extract similarity characteristics. These characteristics can then be used to compare workpieces and determine the degree of similarity.
This work presents a completely different approach to the discussed problem. Artificial neural networks are used for mapping workpiece properties to the ideal CT measurement parameters.

Figure 1: An Artificial Neural Network consisting of three layers, two input neurons and one output neuron.

2 Radial Basis Function Neural Networks for parameter prediction
The aim of this work is to develop a system based on Radial Basis Function (RBF) neural networks that maps workpiece properties onto the optimal scan parameters.

2.1 Artificial Neural Networks
Originally, an Artificial Neural Network (ANN) [4] is a computational model based on the functional principles of biological processes in the brain. It is composed of artificial neurons, which are highly interconnected and commonly arranged in layers. A neural network can be graphically represented as a directed graph. A simple ANN often consists of three layers. The input layer receives information and passes it on via the connections to a hidden layer which in turn passes it on to the output layer. The connections are annotated with weights, which - together with information communicated via the connections - provide the input for the artificial neuron they are connected to. An artificial neuron is equipped with a net input and an activation function. It processes the input and then transmits its activation to other neurons.

An ANN can be used to implement a function $f: X \rightarrow Y$, where the cardinality of $X$ equals the number of input neurons and the cardinality of $Y$ equals the number of output neurons, respectively. Before an ANN can operate it has to “learn” the function implied by the sample data. In the so-called training phase, the network is presented with a set of sample data $(x, t)$, where $t$ (the so-called target) is the desired output vector for input vector $x$. By applying a training algorithm, the ANN can “learn“ the function implied by the sample data. That is, it minimizes the deviation of the actual output $y$ from the target $t$ by means of an appropriate error function.

Whereas the number of input neurons and output neurons is specified by the problem definition, the size of the network (i.e., the amount of hidden layers and hidden neurons) can be chosen freely. The optimum size of an ANN has to be determined carefully. On the one hand, a network has to be flexible enough to be able to predict the training data sufficiently. On the other hand, there is the danger of over-fitting the data if the network is too complex, meaning that the network will perform very well on the training data but poor on previously unseen data (generalization). This can be avoided by partitioning the training data into a training set and a validation set. Different networks are
subsequently trained on the training data and their predictive performance is then compared on the validation set. The ANN which performs best on the validation data is chosen. This approach is known as cross-validation. If only a small amount of sample data of size $N$ is available then the so-called leave-one-out method can be applied, in which the networks are trained on a subset of size $(N-1)$ and validated on the remaining data point. This is done for all subsets of size $(N-1)$, resulting in $N$ training runs per ANN. The results are then averaged over all runs.

2.2 Radial Basis Function Networks

The type of network used in this paper is known as a radial basis function (RBF) network [4]. Such a network is a special type of ANN, typically consisting of three layers, an input layer $I$, a hidden layer $H$ and an output layer $O$. The input layer passes the external input $x$ on to the hidden layer without any modifications. The activation $a_j(x)$ of hidden neuron $j \in H$ is then determined by the distance $d_j(x) = \|w_j - x\|$ between the input vector $x = (x_1, x_2, ..., x_n)$ and the weight vector of the neuron’s incoming connections $w_j = (w_{(1,j)}, w_{(2,j)}, ..., w_{(n,j)})$. This distance serves as the input for the hidden node’s radial basis function. The most common choice for such a basis function is the Gaussian

$$a_j(x) = e^{-\|w_j\|^2 / r_j^2}$$

where the parameter $r_j$ is also known as the radius and the weight vector $w_j$ is known as the center of the function. The output of neuron $k \in O$ equals its activation $a_k$ and is taken to be a linear combination of the basis functions

$$a_k(x) = \sum_{j=1}^{|O|} w_{(k,j)} \cdot a_j(x)$$

RBF networks have the property of universal approximation, basically meaning that an RBF network can approximate any continuous function to arbitrary accuracy. Moreover, training procedures for RBF networks exist that are significantly faster than methods used for training other types of ANNs [5]. In comparison to other modeling techniques that may be functionally equivalent such as support vector machines, fuzzy systems, or probabilistic models, RBF networks offer the advantage that the training process may be varied to control the semantics of the trained network, i.e., to give the network a generative or discriminative behavior, for instance [6].

2.3 Experimental Setup

As mentioned before, ANNs require training data for which the outputs for given inputs are known. Thus, in order to predict the optimal parameters for workpieces, the system has to be trained on workpieces for which the optimal parameters are known. These data can be obtained, for instance, by applying any of the methods described in the introduction.

In this work, a series of automatic CT measurements was performed for steel cylinders of different diameter. The measurement series were carried out by a DMIS program, which systematically performs measurements with different parameter settings. In total, more than 500 individual measurements were performed. While voltage, current and exposure time were varied, all other parameters were kept constant. An aluminum filter of 1.00mm thickness was used and the applied magnification was 15.79.

The measurements were performed on the TomoScope HV500 cone-beam CT scanner (Werth Messtechnik GmbH, Gießen, Germany) and evaluated using the Werth software WinWerth. The
optimal CT scan parameters for the cylinders were found by determining the diameter of the individual measurements at five equidistantly distributed levels. The average deviation of these diameters from their true values then serves as a quality criterion. The parameters for the measurement with the lowest average diameter deviation for a given cylinder were then taken as the optimal scan parameters for the specimen.

Table 1 shows the diameters of the steel cylinders and their corresponding optimal parameters, which were found in the measurement series.

<table>
<thead>
<tr>
<th>diameter (mm)</th>
<th>current (µA)</th>
<th>voltage (kV)</th>
<th>exposure time (ms)</th>
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<tr>
<td>1.01</td>
<td>200</td>
<td>75</td>
<td>666</td>
</tr>
<tr>
<td>2.50</td>
<td>150</td>
<td>150</td>
<td>333</td>
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<tr>
<td>3.00</td>
<td>100</td>
<td>150</td>
<td>500</td>
</tr>
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<td>225</td>
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</tr>
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<td>4.00</td>
<td>100</td>
<td>225</td>
<td>285</td>
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<td>4.50</td>
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<td>225</td>
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<tr>
<td>10.00</td>
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<td>225</td>
<td>666</td>
</tr>
</tbody>
</table>

Table 1: Diameter and corresponding optimal CT scan parameters of the various steel cylinders.

### 2.4 Applied RBF Neural Networks

In this work the WEKA implementation of RBF networks [7] is used. The training phase of the network is divided into two stages. In the first stage, the centers as well as the radii of the basis functions are determined by the \textit{k-means clustering} algorithm [8]. After that, linear or logistic regression [9] is applied, depending on whether the network outputs represent the values of continuous variables (regression problem) or discrete variables (classification problem).

In order to predict the optimal current, voltage and exposure time settings, three separate RBF networks will be employed. Every network receives a cylinder diameter and maps it onto one of the three parameters. Because of the small amount of sample data, the leave-one-out method will be applied to find the optimum network size.

### 3 Results

Figure 2 show the results of the leave-one-out methods for all three networks. The root mean square error (RMSE) of the individual RBF networks is plotted against the number of hidden neurons, ranging between one and fifteen. The amount of hidden neurons which leads to the lowest RMSE for a given network is then chosen.

The optimal size for the current predicting network and the exposure time predicting network amounts to 14 hidden neurons. The network for the prediction of voltage performs best with 8 hidden neurons. While the corresponding networks for current and voltage prediction have the similar RMSE values of 23.73 and 23.74 respectively, the exposure time predicting network performs a lot worse, having an RMSE of 147.15. It can be observed, that both the current predicting network as well as the exposure
time predicting network have a low RMSE value for three hidden neurons. Because of the danger of over-fitting the data it would also be an option to choose this number of hidden neurons over the 14 neurons, for which the error is smallest. However, in the following only the case of 14 hidden neurons will be examined.

After having determined the optimal number of hidden neurons, the trained networks can be used for predicting the individual parameters.

In Figure 2 the leave-one-out method applied to current predicting network (upper left), voltage predicting network (upper right) and exposure time predicting network (bottom left).

In Figure 3 the optimal and predicted parameter values are plotted against the cylinder diameters for all three networks. It can be seen, that both current and voltage are predicted quite well. The parameter exposure time on the other hand imposes greater difficulties on the applied RBF network, as was indicated by the higher RMSE value.

The predictions of all three RBF networks are shown in Table 2 along with their corresponding optimal parameters, i.e., the parameters found in the measurement series. Because exposure time is a discrete parameter, the predicted values have been rounded to the next higher or lower achievable value.
As an estimate of how well measurements with the predicted parameters would perform on the CT scanner, the predicted parameter combinations are compared to the parameter combinations in the measurement series for a given cylinder. The quality (i.e., the average diameter deviation, as explained in Section 2.3) of the most similar combination is compared to the quality of the best measurement in the series and the difference between both values serves as an indication of the overall quality of the
predicted parameter combinations. The smaller the result of this difference (shown in column “error difference of Table 2) is, the better the CT measurements with the predicted parameters are assumed to be. A value of 0 means, that a measurement with the predicted parameters is assumed to perform just as well as a measurement with the optimal parameter combination (based on the results of the measurement series).

The most similar combination (based on the Euclidian distance) in the series is chosen by the $k$-nearest neighbor algorithm [8] for $k = 1$.

4 Conclusion and Outlook

In this work, a new approach for finding optimal CT parameters was examined. Radial Basis Function networks were used for the determination of the parameters, based on the diameter of the investigated steel test cylinders. It could be shown that RBF networks constitute a suitable means for this task, while its predictive qualities depend on the parameter under investigation. It should be mentioned that because of the time-consuming process for acquiring training data, the amount of data used for the present study is still too low to allow for very general conclusions. Thus, the results presented here should be seen as promising, but still preliminary.

As the performance of Artificial Neural Networks depends greatly on the amount of training data, one of the main tasks for future work will be to generate more of these data. Additionally, some more parameters will be investigated, such as filter type or material. For practical purposes, also more complex workpieces than cylinders will be examined.

From the viewpoint of ANN, it seems to be promising to investigate the prediction of parameters in a hierarchical fashion or the prediction of parameter combinations. Thus, existing expert knowledge about the application domain could be fused with knowledge automatically extracted from sample data by means of training algorithms. Moreover, the obviously multi-modal character of the (here implicitly given) objective function – namely the minimal deviation of measured object geometry from the actual object geometry – could be considered appropriately. Other classification and regression techniques will be considered as well.

The final goal of the present work is to provide a tool that (1) automatically selects optimal scan parameter combinations in “standard situations” where workpieces are “sufficiently” similar to ones investigated earlier and (2) guide the human operator interactively in “non-standard situations” in finding optimal parameter values in an efficient and effective way.

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References


