MODELLING AND INTERPOLATION OF SPATIAL TEMPERATURE DURING FOOD TRANSPORTATION AND STORAGE BY THE VARIOGRAM

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ABSTRACT

A better control of food transport, storage and processing is achieved if single-point temperature measurements are replaced by spatial monitoring. The statistical temperature distribution inside a room is described by a Variogram model. The temperature for any point in space can be interpolated by the Variogram based Kriging method. The accuracy of the Kriging method was tested on 14 experimental data sets recorded in cold-storage rooms, delivery trucks, and containers. The interpolation error can be reduced by up to 68% compared to an average measurement. Kriging showed also a clear advantage over the Inverse-Distance-Weighting interpolation method, with a higher reduction of the error by 20% except for 4 data sets with an insufficient spatial sensor density. Different approaches for automated estimation of the Variogram model parameters were compared. The influence range of temperature deviations was evaluated to values between 1.1 and 4.7 meter, depending on the air-permeability of the food packing.

Keywords: Variogram modelling, Kriging, spatial interpolation, temperature supervision

1. INTRODUCTION

Local temperature deviations during the processing, storage and transport of foods can degrade their quality. Our measurements showed that temperature cannot be considered as constant over space; the temperature profile shows a number of cold and hot spots, which influence their neighbourhood within a certain range.

Because the number of available sensors is limited in practical applications, the temperature for points in between the sensors has to be calculated by interpolation. The Kriging method provides a statistically correct interpolation. Aim of this paper is to test the performance and accuracy of this method for typical spatial temperature supervision tasks in food logistics on recorded data sets of 14 experiments, carried out in cold storage rooms, delivery trucks and containers.

The first step of the Kriging method comprises of a statistical analysis of the given measurements. A so-called theoretical Variogram model is derived from the experimental data, describing the relation between expected temperature deviation and the distance between the probe points. There is only a small set of mathematical functions, which are typically used as Variogram models, sharing the same parameters: nugget, sill, and range.

The nugget gives the deviation that should be expected even for small distances caused by noise, sensor tolerances, and border effects. The expected deviation increases within the Variogram range but stays almost constant afterwards at the sill value. If the probe area is large enough, the variance of all measurements can be taken as a raw estimation for the sill value.

The following section will briefly introduce the Variogram and the Kriging method. It also defines the test method to evaluate the interpolation error. Section 3 will introduce different approaches for an automated estimation of the Variogram parameters.

Our experimental database is described in Section 4, consisting of 8 sets recorded in a cold storage room either empty or loaded with 2 tons of water bottles to simulate food storage. Six further sets were recorded during regular food transports.

The size of the influence range of temperature deviations depends very much on the air permeability of the cargo. Range of values between 1.1 and 4.7 meter were found depending on the type of cargo (Section 5).

The evaluation of the interpolation accuracy in Section 6 showed that the Kriging interpolation reduces the prediction error by 35% to 68% for the tests in cold storage rooms and trucks, compared to a Null-model that ignores spatial dependency and takes the average sensor measurements as temperature prediction. But the interpolation of the container data sets hardly showed any improvement. An index value to evaluate whether a given sensor density is sufficient for reliable interpolation was derived from the data sets.

The spatial interpolation shall be integrated into an intelligent container for fully automated supervision of food transportation. The required telemetric system and an automated shelf life evaluation is currently developed as a separate focus of our project. Our evaluation of the required CPU recourses in section 7 showed that the Kriging method is fully capable of running on embedded systems that could be integrated into a truck or a container.

2. BACKGROUND OF THE KRIGING METHOD

Kriging (Wackernagel 2003; Schabenberger and Gotway 2005) applies a linear interpolation to predict the temperature in one destination point by multiplying the available measurements with a set of weighting factors. There are some heuristic methods to set the weighting factors such as the Inverse-Distance-Weighting (IDW). The application of the Variogram to set the Kriging weights provides a statistically correct estimator for the weighting factors, and therefore, is the best linear estimator under the condition that the expected value for the difference between two points depends only on their distance vector and not on their absolute position. The Kriging method originates from Geology, but it has been adapted to sensor measurements in food transports in our previous publication (Jedermann and Lang 2009).

An experimental Variogram is calculated from the measurements and then fitted with a theoretical model. The Spherical model and the Gauss model gave the best results for our tests. The model parameters are selected in a way to minimize the error between experimental and theoretical Variogram Φ.

2.1. Method for evaluation of the interpolation error

The experimental data sets were split into a set of source points as input for the interpolation and a set of destination or reference points. The measurement of the latter set was compared with the result of the interpolation.

The error of the interpolation ε was calculated as Root-Mean-Square difference between the interpolated prediction and the actual measurement over all sampling intervals and destination points.

Because of sensor tolerances and the nugget effect, it is not possible to reduce the interpolation error to zero. The interpolation error of the Kriging method was compared with two other prediction methods as reference.

The Null-model assumes that there is no dependency between location and measurement. For this case, the only possible way is to take the average of all available measurement locations as predictions for all destination points. The mathematically simpler Inverse-Distance-Weighting was used as the second reference method.

The Kriging method does not only provide a prediction for the destination points, but it also estimates the standard deviation $\sigma_k(i)$ of the prediction for any destination point i.

Furthermore, the general accuracy of the Variogram and the Kriging method can be evaluated by comparing the average relation θ between the predicted Kriging standard deviation $\sigma_k(i)$ and the actual error $\varepsilon(i)$ for each destination point i as suggested by Wackernagel (2003).

The relation should be about 1; otherwise, the Variogram model could be inaccurate, the temperature distribution could contain an anisotropic dependency that has not been considered, or the temperature differences could depend on absolute positions and not only on the distance vector.

3. METHODS FOR AUTOMATED VARIOGRAM ESTIMATION

A fully automated system for transport supervision has to adapt the Variogram parameters range, nugget and sill to the experimental data without human interference. Three unsupervised methods were tested and compared according to their stability, computational efficiency, resulting interpolation error ε, and test of the relation θ.

3.1. Grid search

As the first attempt, a *brute-force* grid search was implemented. The grid search tests all combinations of range, nugget and sill for the lowest fitting error Φ between a given set of boundaries. This method turned out to be very stable. For an adequate setup of the boundaries, the variance of all measurements σ_M^2 is taken as raw estimation of the sill. The grid search tested for values between 60% and 180% of the measurement variance σ_M^2.

The nugget must be smaller than the sill; otherwise, the Variogram model does not increase monotonically. But, we found that the nugget values of zero as well as too-high values can lead to a poor relation θ. Therefore, the lower and upper grid boundaries for the nugget value were set to 2% and 20% of the measurement variance σ_M^2, respectively. The boundaries for the value of the Variogram range were rather uncritical; therefore, the grid search tested for values between 1 and 10 meters.

3.2. Nelder-Mead algorithm

A more efficient Variogram fitting algorithm was found in (Schwanghart 2009). He provides a Matlab script to minimize the fitting error Φ to an experimental, isotropic Variogram. However, the minimum is not found by the least squares method, instead, it uses the algorithm from Nelder and Mead (1965), which is a heuristic, well-known method to be effective and computationally compact as it does not need any matrix inversion.

Furthermore, it provides additional advantages that may improve the good fitting of the function: it allows weighting the least squares if the number of observation per experimental lag is provided. Two weighting schemes are selected from Geostatistics literature. The first one is based on Cressie (1985). It automatically gives most weight to early lags and down-weights to those with small number of lags; the second one, which makes use of the Akaike information criterion as a measure of the goodness of the fit, is based on McBratney and Webster (1986).

3.3. Fixed Variogram parameters

The sill depends very much on the experimental conditions such as initial temperature differences at loading, whereas the range and nugget have only little variations for transports with similar loading schemes. Based on this observation, a further method for parameter estimation was created that adapts only the sill value to the actual experiment. Our database was divided in to 5 groups according to the type of cooling and loading scheme. The experiments of each group shared the same nugget and range values.

The range was set to the average value of the previous experiments belonging to the same group. Because of the problems defining the boundaries for the nugget value, we tried to set the nugget directly by physical considerations. The nugget depends, among other factors, on the tolerance of the sensors. The nugget was directly set to the square of the measured sensor tolerances.

The sill was calculated to fit the average value of the theoretical model to the experimental Variogram for large distances. The number of required mathematical operations was thereby largely reduced. Furthermore, the accuracy of the experimental Variogram is less critical because only the average is required.

4. EXPERIMENTAL DATABASE

Eight data sets were recorded by three authors of this paper at the wall-sides of a cold storage room (Rodríguez-Bermejo, Barreiro, Robla and Ruiz-García 2007). The measurements were taken in one compartment with the size of 2.6 × 2.2 × 2.3 meters with 54 or 68 PT100 probes. Figure 1 (top) shows the typical temperature distribution at the walls. Three dual-state conditions were combined to make up the 8 experiments. The conditions are loading state (empty/full), set point (0°C/6 °C) and type of cooling (on-off /modulated).

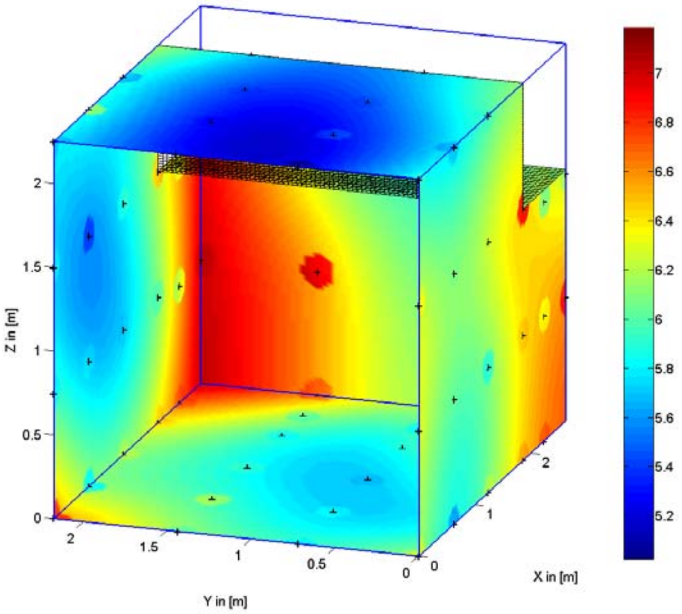
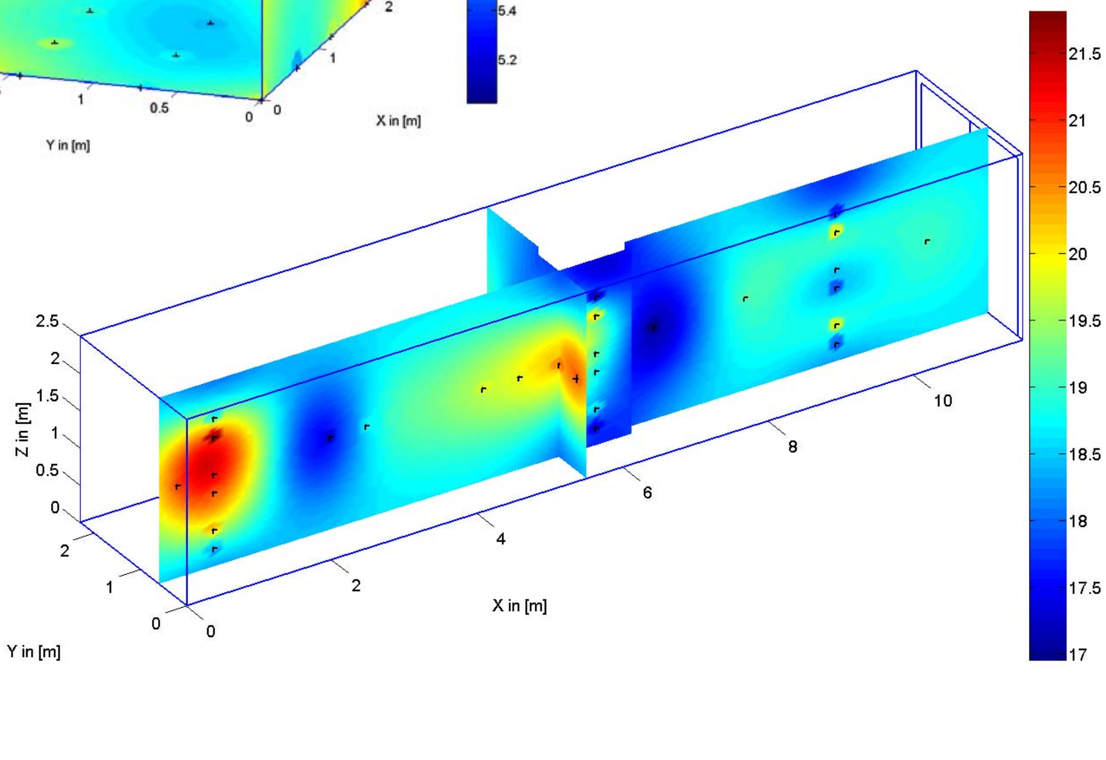


Figure 1: Average temperature over time for experiments 6 (top, loaded cold storage room, set point 6 °C) and 14 (bottom, container loaded with bananas, set point 14.4 °C). The sensor positions are marked with a cross. The surface temperature was interpolated with Kriging.



Further data sets were recorded in delivery trucks by the first author of this paper (Jedermann and Lang 2009) in cooperation with Rungis Express, which is a German food supplier for hotels and restaurants. The trucks had 3 separate chambers or temperature zones. Two sets (Experiment 9 and 10) were recorded in the deep freezer chamber with a size of 2.9 × 2.5 × 2.35 meters at a set point of -29°C. The compartment was partly filled with frozen meat in air-permeable boxes. In 2009 a first test of the Kriging method was carried out with these two data sets, but the results are not directly comparable because of the now refined method for evaluation of the interpolation error and the modified error criterion.

In further tests, the data loggers were not placed at the walls but inside the freight. Two data sets from a sea transport of bananas with 45 sensor positions were provided by Maersk (Experiment 11 and 12). Two sets were recorded by the first author of this paper in cooperation with Dole on banana transports from Costa Rica to Europe in 2010 and 2011. Twenty-seven iButton data loggers were packed in the centre of the banana boxes for the experiment 13 and 31 loggers for the experiment 14. Because the bananas inside the boxes were packed in a plastic bag to prevent humidity loss, the air could only flow through small gaps between the pallets.

5. RESULTING VARIOGRAM MODELS

Table 1 shows the average range of the grid search Variogram models sorted by groups of experiments. The average range values were used as parameters for the fixed models. The Table indicates that the range depends on the packing of the loaded cargo. If the air can circulate freely in the room, temperature distortions can spread over a wider range by convection. The highest range of 4.7 metre was measured in empty cold storage rooms. Partially filled cold storage rooms (Figure 2) and trucks (Figure 3) showed almost the same range of 3.25 to 4 meter. For densely packed cargo such as bananas in sea containers (Figure 4) the range dropped to 1.65 or 1.125 meter.

The experimental Variograms for the container tests turned out to be very noisy which might be caused by anisotropic dependencies of the variance from the direction of the distance vector between the pair of points. But the number of available probe points in the container tests was clearly insufficient for an analysis of anisotropic effects.

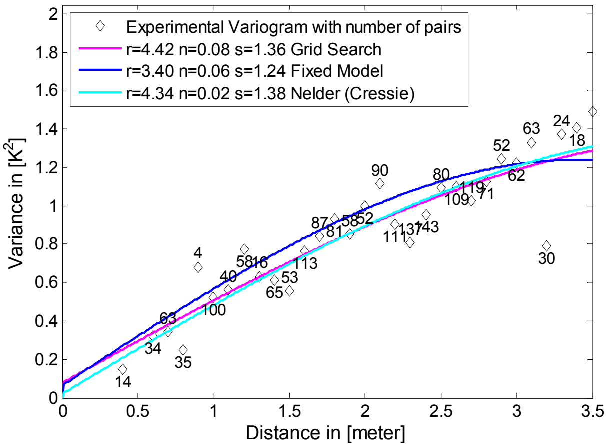


Figure 2: Experimental Variogram for experiment 8 (loaded cold storage room) and Spherical models resulting from different estimator algorithms.

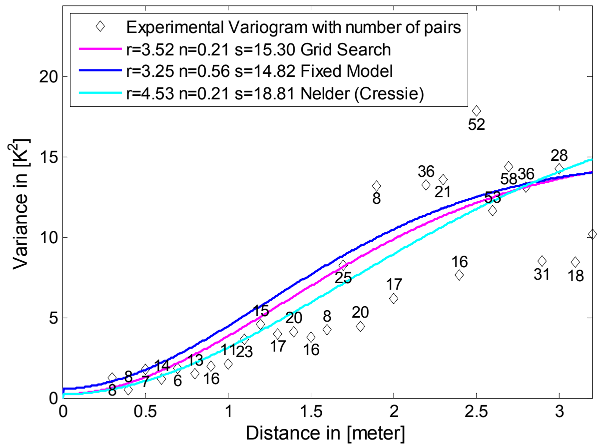


Figure 3: Gauss Variogram for partly filled truck (experiment 10)

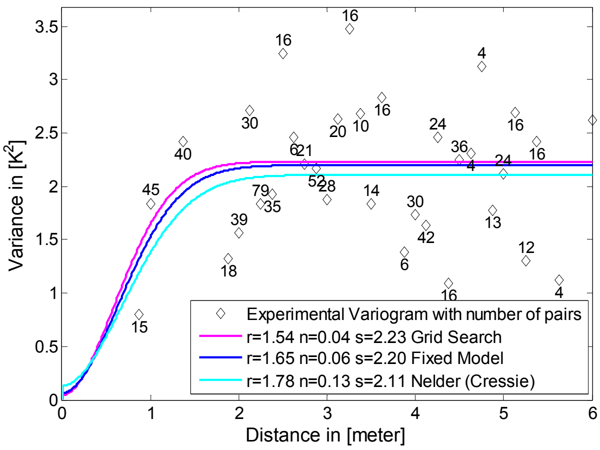


Figure 4: Gauss Variogram for sea container loaded with bananas (experiment 11)

6. EVALUATION OF INTERPOLATION ACCURACY

The Kriging interpolation was calculated based on the resulting Variogram parameter for the grid search, the fixed model and for the Nelder/Cressie search algorithm. The prediction error for the Kriging interpolation was compared with the Null-model and the Inverse-Distance-Weighting model as reference in Figure 5.

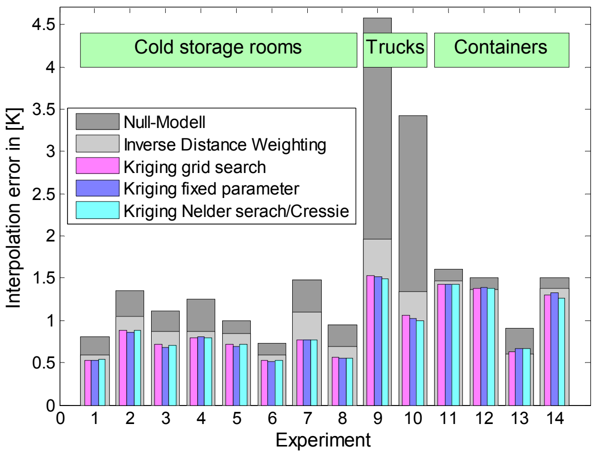


Figure 5: Error between prediction and measurements for different methods for Variogram estimation. Compared with the Null- and the IDW-model.

The highest reduction of the interpolation error was achieved for the truck tests by Kriging. The tests in the cold storage room showed a smaller but still remarkable improvement compared with the two reference models. But the Kriging method brought only very little advantage compared to the Null-model and was sometimes even worse than the Inverse-Distance-Weighting for the container tests. The selection of the method for estimation of the Variogram parameters had only a negligible effect on the interpolation error.

Therefore, the best method was selected based on the relation between Kriging Variance and actual interpolation error θ, given in Figure 6. The relation for the tests in the cold storage room almost arrived at the target value of 1. But for the last two container experiments at Dole the relation increased to values of up to 3.5. This is a further indication that the interpolation is inaccurate for the containers with the current sensor setup. But this does not mean that the interpolation is not possible for densely packed containers, or that there are no spatial dependencies of temperature, but merely that a higher number of sensors are required.

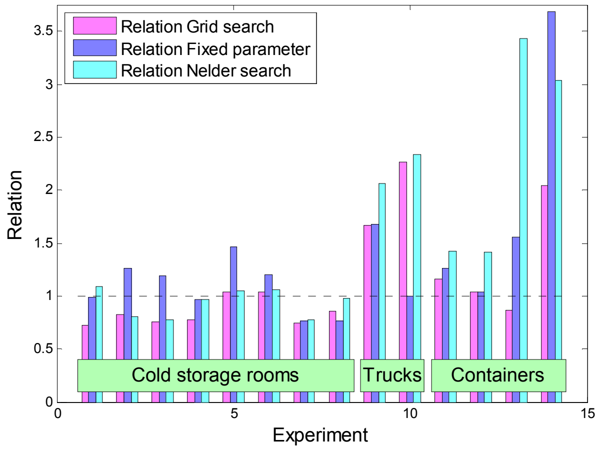


Figure 6: Relation between Kriging Variance and actual interpolation error θ for different methods for Variogram estimation.

Depending on the type of experiment, different methods for Variogram estimation gave the best result for the relation θ. The selected methods are summarized in Table 2. The interpolation error can be reduced by up to 68.5 % if Kriging is used for interpolation compared with the Null-model. Compared with the Inverse-Distance-Weighting, the Kriging interpolation is in average 20% better except for the container tests.

The weighting according to McBratney and Webster (1986) was rejected because it gave only inaccurate Variogram parameter for two tests in the cold storage room. Furthermore, the relation was worse than by all other methods.

Table1: Fixed range parameter for groups of experiments. For the number of neighbours in range see section 6.1.

Group	Range	Model type	Neighbours in range
Empty cold storage room	4.7 metre	Spherical	29.9
Loaded cold storage room	3.4 metre	Spherical	24.7
Truck, partly filled	3.25 metre	Gauss	24.5
Container Maersk, inside bananas	1.65 metre	Gauss	3.8
Container Dole, inside bananas	1.125 metre	Gauss	4.0

Table 2: List of methods that gave the best relation θ for the different types of experiments.

Type	Best method	Model type	Improvement over Null-model	Improvement over IDW-model
Cold storage room	Nelder/Cressie	Spherical	35.8 %	16.0 %
Truck	Fixed parameters	Gauss	68.5 %	23.4 %
Container	Grid search	Gauss	16.1 %	1.4 %

6.1. Index for sensor density

The question arises why the interpolation gave such a poor result for the container experiments although a similar number of probe points were used. But, the difference between the types of experiments becomes obvious if for each destination point the number of neighbouring source points within the Variogram range is counted. This number is important because the source points with a distance lower than the Variogram range have the most influence on the interpolation result.

The cold storage rooms and trucks had an average number of *neighbours in range* between 24 and 30, whereas the sensor setup for the containers had only 3.8 or 4 neighbours in range as listed in Table 1.

The number of neighbours in range can be taken as an index value to evaluate whether a proposed sensor setup is sufficient for interpolation.

In order to estimate a threshold for the index value, the number of source points was incremented step by step in Figure 7. The horizontal axis was recalculated in order to directly display the number of neighbours in range instead of the total number of source points.

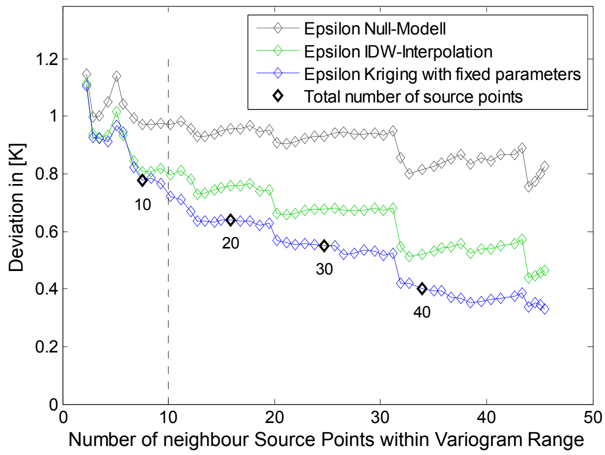


Figure 7: Interpolation error as function of the number of neighbours in range for experiment 8 (loaded cold storage room). Total number of source points marked by diamonds.

If the number of neighbours in range is higher than 10 (dotted line in Figure 7), the Kriging interpolation results in a lower error than the Inverse-Distance-Weighting. At this index value, Kriging has also a clear benefit compared to the Null-model.

7. EMBEDDED KRIGING ON INTELLIGENT SENSORS AND CONTAINERS

So far, Kriging was considered as an offline tool to analyse recorded data sets, but the paramount aim of our project is to obtain real-time information during transport. Measurement data should be directly processed within the means of transportation or even by the sensors themselves.

Besides the Kriging interpolation several other approaches for local data processing were evaluated within our project, including calculating the effects of temperature deviations on the product quality by a shelf life model and predicting the future temperature development of a cool-down process by a system model (Palafox et al. 2011). We consider wireless sensor nodes not only as a tool for remote data acquisition, but as a platform for decentralised decision making. But, it has to be questioned whether the CPU resources of wireless sensor platforms are sufficient to execute complex algorithms.

The Variogram estimator and the Kriging interpolation were implemented as Java software bundles and tested on the iMote2 sensor with a PXA 271 ARM X-Scale processor (Crossbow 2007), used as a pilot platform. The estimation of the theoretical Variogram turned out as the most CPU-resource consuming task. The measurements showed clear advantages of the Nelder-Mead algorithm, which required only 32 seconds of CPU time, whereas the Grid-Search required more than 4 minutes. The calculation of a Kriging weighting matrix for 20 destination points was much faster with only 2 seconds of required CPU time.

Although the processor is occupied for a longer period of time during the initialisation of the Kriging interpolation, this has only a little effect on the average load because the initialisation is required only once per transport. Tasks that need to be executed once for each sampling interval can be more critical. But, the application of the weighting matrix took only 17.5 ms per sampling interval for a set of 20 sensors. The Kriging method is therefore fully suitable to run on embedded systems such as wireless sensor nodes.

The Kriging method can provide an estimation of the temperature in any point of space under the precondition that the spatial sensor density is high enough for interpolation (see section 6.1). The higher mathematical complexity of the Kriging method compared with simpler methods such as the Inverse Distance Weighting is rewarded with an improved accuracy, which is 20% better in average. Furthermore, the accuracy of the Kriging method depends on correct estimation of the Variogram model parameters. Best results were achieved either by the Nelder-Mead algorithm combined with the weighting according to Cressie or by setting the nugget by known sensor tolerances and the range by an average value of previous experiments.

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