Method of Soil Moisture Measurement by Impedance Spectroscopy with Soil Type Recognition for In-Situ Applications (Messverfahren zur Bodenfeuchtemessung mittels Impedanzspektroskop...

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Method of Soil Moisture Measurement by Impedance Spectroscopy with Soil Type Recognition for In-Situ Applications

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Soil moisture sensor systems need extensive calibration processes because of the dependence on soil properties. A novel measurement method is presented which is based on impedance spectroscopy. This method takes advantage of impedance spectroscopy for the characterization of soil type and measurement of soil moisture with improved accuracy. A comprehensive compensation of cross-sensitivity effects is carried out. The soil type characterization was carried out by a multivariate analysis based on elaborated experimental investigations of different natural soils. The results show that the new measurement method provides a measurement accuracy that fulfills the requirements of respective applications.

Keywords: Soil moisture measurement, impedance spectroscopy, compensation of influence effects, principal components analysis, *k*-nearest neighbour method

Messverfahren zur Bodenfeuchtemessung mittels Impedanzspektroskopie mit Bodenarterkennung für In-situ-Anwendungen

Sensorsysteme für die Bodenfeuchtemessung brauchen extensive Kalibrierungen aufgrund der meist deutlichen Bodenartabhängigkeit. In diesem Beitrag wird ein neuartiges Verfahren zur Bodenfeuchtemessung, basierend auf Impedanzspektroskopie, vorgestellt. Dabei werden die Vorteile der Impedanzspektroskopie gezielt dazu eingesetzt, um die Bodenart in-situ zu erkennen und deshalb die Bodenfeuchte genauer zu messen. Eine eingehende Behandlung unerwünschter Effekte wurde durchgeführt. Zur Bodenarterkennung wurde ein Verfahren der multivariaten Analyse eingesetzt, basierend auf ausführlichen experimentellen Ergebnissen mit verschiedenen natürlichen Bodenarten. Die Ergebnisse zeigen, dass das neue Messverfahren eine Messgenauigkeit erzielt, die die Anforderungen der Anwendung erfüllt.

Schlagwörter: Bodenfeuchtemessung, Impedanzspektroskopie, Kompensation, Hauptkomponentenanalyse, *k*-nearest-neighbour-Methode

1 Introduction

The knowledge of the water content of soil is fundamental for improving the effectiveness of irrigation processes with respect to both costs and environmental aspects. In practice, the abuse of water resources is generally accompanied by a reduction of effectiveness and on long-term even leads to a contamination of soil and ground water. An accurate in-situ moisture measurement is important for environmental monitoring as well as for several applications in civil engineering.

Several methods are available for in-situ water content measurement [1]. Capacitive sensors can be preferred because of their low-cost and easy use. Other methods such as Time Domain Reflectometry (TDR) or microwave methods are more accurate but expensive for low-end applications. Most in-situ methods of soil moisture measurement require calibration to eliminate the effect of soil type. Without calibration errors of more than 5% Volumetric Water Content (VWC) are encountered in moisture measurements [1].

In [2] it is proposed to use impedance spectroscopy. This method has advantages because of the possibility to use capacitive and resistive parts of soil impedance at different frequencies, which allows the elimination of the dependence on soil properties and therefore reduces the calibration effort [3].

2 Experimental Investigations

Laboratory analysis of soil under well-controlled conditions is time consuming. Soil samples are completely dried and than mixed with a certain amount of water in order to realize a soil moisture level. The soil density influences measurement results [4] and preparing a soil probe with a certain density is difficult and may require several attempts. Additionally complete drying of soil can change the soil properties. It is also difficult to maintain the same density in different experiments. The results are therefore only reproducible if measurements are carried out with particular care.

To overcome these imperfections an automatic measurement set-up is developed. The soil is placed within a stable reservoir (Fig. 1) and is saturated with water at the beginning. Borings on its surface allow water effusion and evaporation during the experiment. The measuring electrodes are positioned within the reservoir, so that even the electrical stray field outside the electrodes passes essentially the soil sample.

Measurements are carried out in a climatic chamber with constant temperature and air ventilation. The intention is to simultaneously measure impedance spectra and gravimetric moisture with a scale during soil desiccation, which can take several weeks but delivers reproducible results. Experimental results show, that the soil moisture in the middle of the reservoir (near position 3, Fig. 2) can be approximated by the gravimetric moisture of the whole soil sample after some hours (reservoir, Fig. 2).

The duration of the experiment depends on the soil type and especially on its ability of water accumulation. The smaller the soil particles are the larger is the specific surface of granulation and thus its ability of water accumulation.

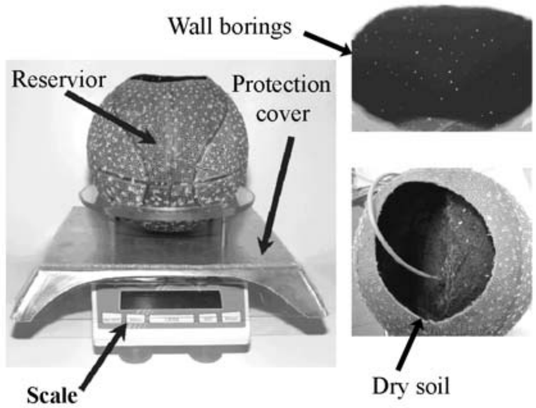

Figure 1: Automatic impedance measurements by uniform soil drying.
Bild 1: Automatische Impedanzmessung bei gleichmäßiger Bodentrocknung.

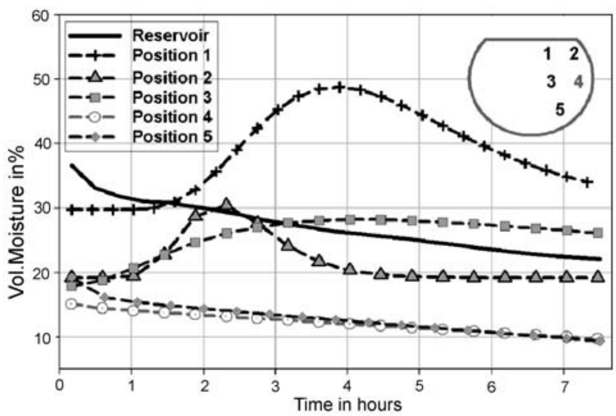

Figure 2: Time dependent behaviour of volumetric water content (θ) in different positions in the measurement reservoir.
Bild 2: Zeitlicher Verlauf von volumetrischer Feuchte in verschiedenen Positionen im Bodenbehälter.

The measurements were carried out at a constant temperature of 30 °C. For coarse sand (GS, Fig. 3) one week is required until the dry state is reached. For soils with more silt and clay contents (MIT & FLO, Fig. 3) the experiments need several weeks until negligible volumetric water content is reached.

The innovative measurement set-up allows measurements in the whole range of volumetric water content relevant for agriculture with good resolution (approx. 0.5%). An important advantage is the similarity to the conditions of the sensor system used in practice. Soil moisture and temperature can be changed without reinstalling the measuring electrodes. Soil density and soil contact stay constant for all moisture levels.

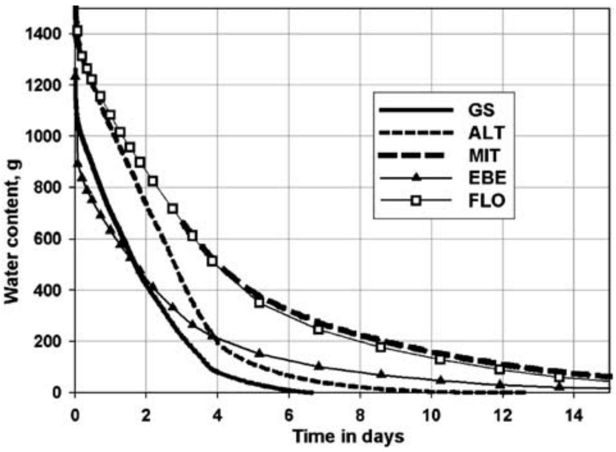

Figure 3: Decrease of gravimetric water content for different soil types over long time period. GS is coarse sand; ALT, MIT, EBE and FLO are natural soils (compositions s. Fig. 4).
Bild 3: Abfall des gravimetrischen Wassergehalts über eine lange Zeit für versch. Bodenarten. GS ist Grobsand; ALT, MIT, EBE und FLO sind natürliche Böden (s. Bild 4).

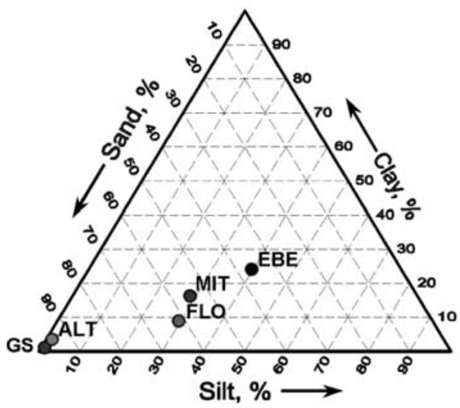

Figure 4: Distribution of the investigated soil types.
Bild 4: Verteilung der untersuchten Bodenarten.

Soils consist generally of organic materials and minerals, which vary in their particle diameter, classified in sand, silt and clay. The investigations described in the next sessions are carried out using measurements with natural soils of different compositions (Fig. 4). The abbreviations chosen correspond to the regions where the soil samples were taken in Germany. These soil samples have well known properties and are therefore suitable for analysis.

3 Investigation of Data Consistency

The data consistency was investigated by means of the Kramers–Kronig (KK) transformation [5; 6]. This transformation dictates the relationship between the real part and the imaginary part of impedance under the assumptions of stability, causality, and linearity [7]. The investigation of data consistency was carried out by the use of a simple measurement model. It consists of a set of in-series connected RC circuits (Fig. 5) resulting in an acceptable fit of the investigated impedance spectrum. The fit of this kind of measurement models can be quite time-consuming. Therefore a sufficient number of τ_i values ($\tau_i = R_i C_i$) has been chosen [8] in advance, so that only the R_i values are to be calculated. These are calculated from the real part in a simple and deterministic way. The choice of start values and running fit procedures can thereby be avoided completely [9].

The application of the Kramers–Kronig transformation on measured data shows good results in the frequency range between 1 kHz and 100 kHz (s. Fig. 6). The deviations in other frequency ranges do not depend on the moisture value (Fig. 6). These result from disturbing electromagnetic fields of cables (s. Sect. 6) and changes of the measurement range by the impedance analyzer.

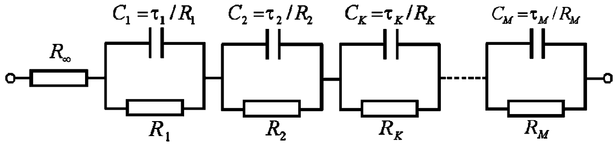

Figure 5: Measurement model for the application of the Kramers–Kronig transformation.
Bild 5: Messmodell für die Anwendung der Kramers–Kronig-Transformation.

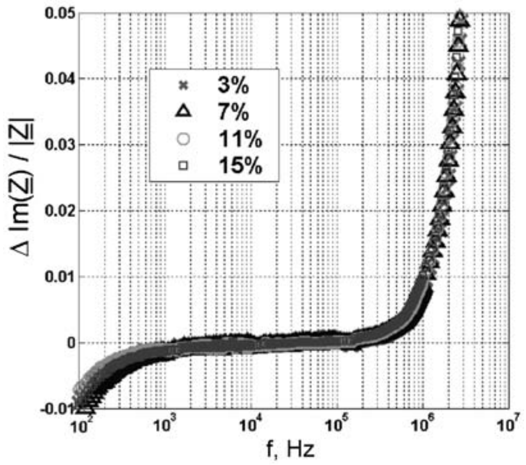

Figure 6: Kramers–Kronig consistency test for coarse sand at different volumetric moistures (6 RC elements per time decade).
Bild 6: Kramers–Kronig-Konsistenzprüfung für Grobsand mit verschiedenen volumetrischen Feuchten (6 RC-Elemente pro Zeitdekade).

4 New Approach for Soil Moisture Measurement

In previous investigations classical methods of signal processing for impedance spectra were applied. They use equivalent circuits for the analysis of the impedance spectrum and parameter extraction [1; 2; 10]. In this case the a-priori knowledge used during in-situ measurement is the equivalent circuit, which should give a good description of the impedance spectrum. The results were parameters which depend on both moisture and soil type.

The novel approach presented in this paper is based on a soil characterization by multivariate analysis before moisture calculation. In this case the a-priori knowledge consists of the experience from measurement data bases gained from various natural soils and collected at the investigation stage by the manufacturer.

Several steps for signal pre-processing and processing are necessary (Fig. 7). The signal pre-processing requires compensation of temperature and cable effects and is described in Sects. 5 and 6.

Principal Components Analysis (PCA), a statistical method, was used for soil characterization (see Sects. 8 and 9). The moisture calculation is described in Sect. 10.

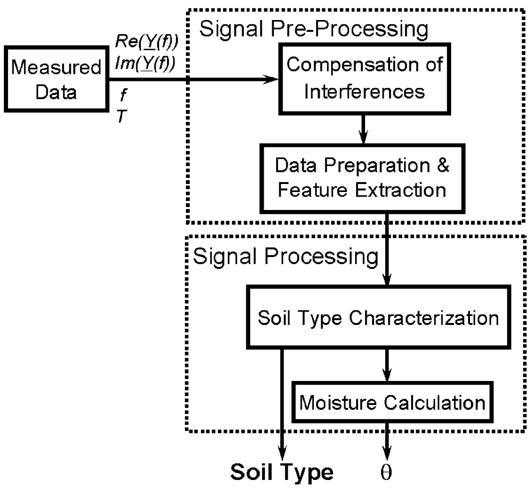

Figure 7: Approach for soil moisture measurement.
Bild 7: Anzatz zur Bodenfeuchtemessung.

5 Temperature Compensation

Investigations show that temperature variations of 10 °C lead to changes of the measured admittance corresponding to changes of soil moisture of approximately 1.5% of soil moisture (Fig. 8). The temperature effect can be well compensated using direct modeling of the influence on admittance.

Temperature compensation was carried out for the real and the imaginary part of the admittance separately in order to achieve better accuracy. A temperature of 29 °C was chosen as the reference temperature.

The temperature influence is modeled using temperature dependent coefficients. The functions used are $B(f)$ and $G(f)$.They can be assumed linear in the

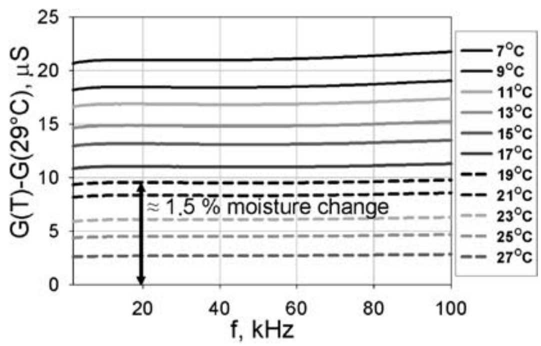

Figure 8: Temperature dependence of the real part of the admittance.
Bild 8: Temperatureinfluss des Realteils der Admittanz.

selected frequency range, so that modeling was carried out as follows:

$$G = G_0 + K_1 \cdot f$$
$$B = B_0 + K_2 \cdot f$$

with G_0, B_0, K_1, K_2: temperature dependent coefficients and $\Delta T = T - T_0$.

The coefficients G_0, B_0, K_1 and K_2 were modeled with cubic polynomial functions in dependence on temperature (Fig. 9).

$$G_0(\Delta T) = a_0 + a_1\Delta T + a_2\Delta T^2 + a_3\Delta T^3$$
$$B_0(\Delta T) = c_0 + c_1\Delta T + c_2\Delta T^2 + c_3\Delta T^3$$
$$K_1(\Delta T) = d_0 + d_1\Delta T + d_2\Delta T^2 + d_3\Delta T^3$$
$$K_2(\Delta T) = e_0 + e_1\Delta T + e_2\Delta T^2 + e_3\Delta T^3$$

Table 1 shows the results of temperature compensation for soil type GS.

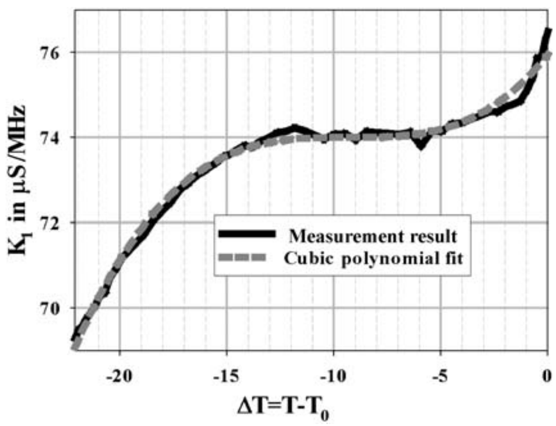

Figure 9: Temperature dependent coefficient K_1.
Bild 9: Temperaturabhängiger Koeffizient K_1.

Parameter	max. rel. error in % without comp.	max. rel. error in % after compensation
G	35.8	0.8
B	8.3	0.8

Table 1: Measurement error due to temperature effect before and after compensation for the temperature range 7 °C–29.3 °C.
Tabelle 1: Messfehler aufgrund des Temperatureinflusses vor und nach der Kompensation für den Temperaturbereich 7 °C–29,3 °C.

6 Compensation of Cable Effects

The results of the Kramers–Kronig test have shown that measurements are consistent in the frequency range from 1 kHz to 100 kHz. Additional tests of measurement accuracy show parasitic effects in the measured signal, that usually happens due to cable influences. Therefore complementary cable-effects compensation are required.

For the compensation of cable-effect, several experiments were evaluated with reference to RCL circuits. Best results were achieved with frequency dependent impedance of the connection cables with open cable ends superposed to the impedance of the device under test in parallel. The impedance was modeled as follows:

$$\underline{Z}_{Meas} = \underline{Z}_{Cable} || \underline{Z}_{Object} = \frac{\underline{Z}_{Cable} \cdot \underline{Z}_{Object}}{\underline{Z}_{Cable} + \underline{Z}_{Object}}$$

where $\underline{Z}_{Meas}$: Measured complex impedance,
$\underline{Z}_{Cable}$: Complex impedance of cable with opened ends,
$\underline{Z}_{Object}$: Complex impedance of the device under test.

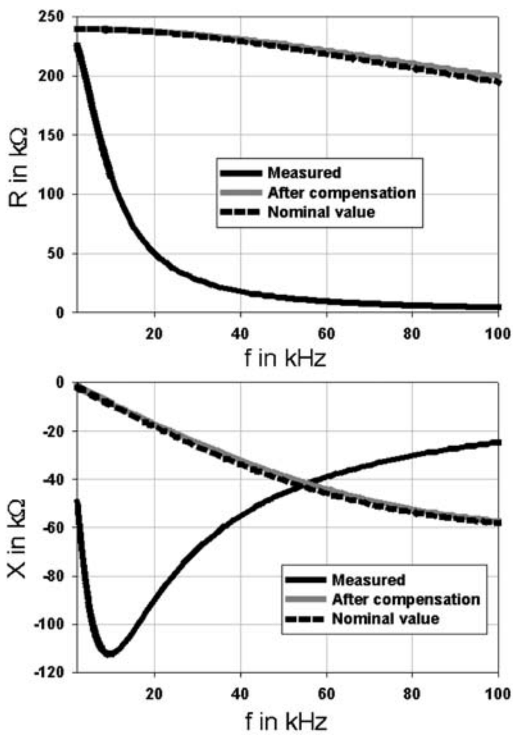

Figure 10: Compensation of cable effect using the frequency dependent impedance of the open ends of the connection cable.
Bild 10: Kompensation von Kabel-Effekten unter Nutzung der frequenzabhängigen Impedanz des offenen Verbindungskabels.

The complex impedance of the device under test $\underline{Z}_{Object}$ can be calculated as:

$$\underline{Z}_{Object} = \frac{\underline{Z}_{Meas} \cdot \underline{Z}_{Cable}}{\underline{Z}_{Meas} - \underline{Z}_{Cable}}$$

Figure 10 shows results of the cable compensation. After compensation the effect of cables the deviations to the nominal values became negligible.

7 Features Extraction

The last step of signal pre-processing is the extraction of relevant signal features to reduce the measurement data to a reasonable number of parameters for subsequent signal processing. For this purpose $|\underline{Y}(f)|$, the real part $G(f) = \mathrm{Re}(\underline{Y}(f))$ and the imaginary part $B(f) = \mathrm{Im}(\underline{Y}(f))$ of the admittance $\underline{Y}(f)$ and dependence were piecewise linearized in dependence of frequency and of each other: $B(G(f))$ in the five frequency intervals:

- $[2, 25]$ kHz
- $[25, 50]$ kHz
- $[50, 75]$ kHz
- $[75, 100]$ kHz
- $[2, 100]$ kHz

The frequency interval $[2, 100]$ kHz is also suitable for future realization with commercially available electronic components.

The signal features chosen are the multiplicative and additive coefficients of the corresponding linear functions in these intervals. Additionally, we considered the values of G, B and $\underline{Y}$ on the boundaries of the frequency intervals in order to minimize the difference between linear and real function.

The entire measurement data including the real and imaginary part of the impedance at several frequencies (362 values for each measurement) is represented by 55 parameters only.

8 Principal Component Analysis

The Principal Component Analysis (PCA) belongs to the statistical methods of multivariate analysis [11]. It is capable to reduce dimensionality of data by eliminating redundancy without significant losses of information content and without needing any physical knowledge about the investigated device. Although this method is in principle useful for processing impedance spectra, it has rarely been applied in this field [12].

Dimensionality reduction of data by PCA is achieved by a transformation of original variables to a new set of uncorrelated variables, the principal components. Generally only few principal components retain most of the variation present in input data [13]. After transformation it is sufficient to analyze only these few principal components without significant loss of information.

For PCA analysis we selected 117 measurements of five soil types at about 23 different moisture values. As described above, for each measurement we calculated suitable 55 parameters for explicit characterization of measurement signals. Therefore, as input for PCA we have a data matrix D with p rows and o columns:

$$D = \begin{bmatrix} d_{11} & \cdots & d_{1o} \\ \vdots & d_{ij} & \vdots \\ d_{p1} & \cdots & d_{po} \end{bmatrix}$$

where $p = 55$: number of parameters and $o = 117$: number of observations.

There are different methods of PCA, such as the eigenvalue decomposition (EIG) and the singular value decomposition (SVD) [14]. Both methods are based on a common principle and have some explicit equivalence. One difference is that the EIG decomposition is carried out for the covariance matrix of the input data. The SVD is carried out for the input data directly and can be preferred because of its computational efficiency and in order to avoid difficulties in the calculation of eigenvalues and eigenvectors for large-sized input matrices.

In the PCA via SVD the input data D is normalized to the matrix:

$$N = \begin{bmatrix} N_1 & N_2 & \cdots & N_O \end{bmatrix}$$

so that the mean values and the standard deviation of all N_i is 1.

Normalization is very important to better use data variance for classification purposes. After normalization, the axes pass through the mean value of the data in the transformed space.

Then the normalized input matrix N is decomposed into three matrices:

$$N = U \cdot S \cdot V^T = U \cdot diag(\sigma_1, \cdots, \sigma_n) \cdot V^T$$

where S: diagonal matrix consisting of positive single values σ_i of the matrix N; U: left singular valued vector matrix of N; V: right singular valued vector matrix of N.

U and V are orthogonal matrices, so that

$$UU^T = U^T U = E$$
$$VV^T = V^T V = E$$

The singular values are sorted in a decreasing order:

$$\sigma_I \geq \sigma_{I+1} \geq 0$$

The number of positive singular values is equal to the rank of data matrix.

The single values of the Matrix N have a direct relationship with the eigenvalues λ_i of the covariance matrix $\Sigma \sim N^T N$:

$$\sigma_i = \sqrt{\lambda_i}$$

The data set is transformed to the new coordinate system as follows:

$$Y = U \cdot N$$

The new coordinates of the data are called principal components or factors. Those principal components, which contribute only to a small amount to the total variance in the data set, may be eliminated without significant loss of information content.

9 Soil Type Characterization by Principal Component Analysis

Preliminary results of the principal components analysis applied to soil type classification are shown in Figs. 11 and 12. We can see that the four first components have a total variance of nearly 100%.

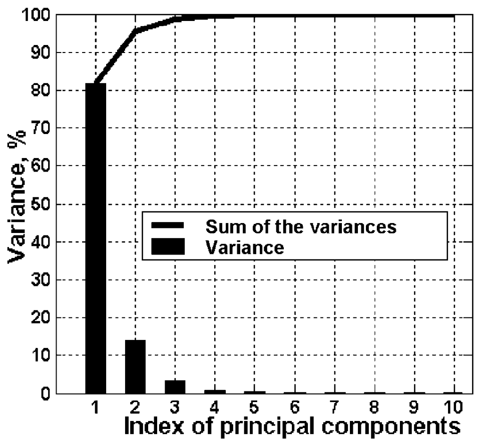

Figure 11: Variance of the first 10 principal components (PC).
Bild 11: Varianz der ersten zehn Hauptkomponenten (HK).

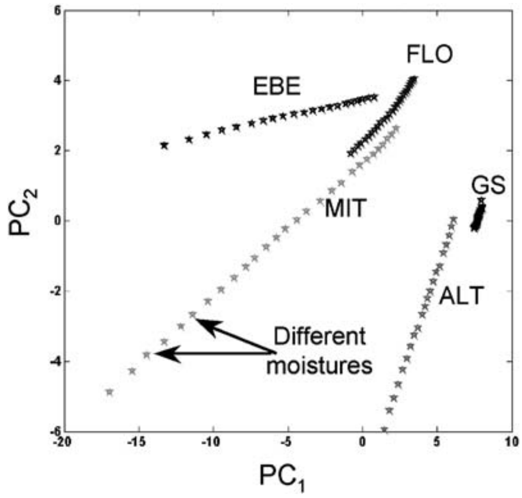

Figure 12: Soil type classification by PCA.
Bild 12: Bodenartklassifikation mit Hauptkomponentenanalyse.

Only the first 2 principal components are sufficient for characterization of the soil type. Figure 12 shows that soil types may be recognized and differentiated from each other. Though no physical knowledge has been considered during signal processing, the classification of spectra correlates with soil composition relative to the silt content of the soil (Fig. 4).

For in-situ measurements it is necessary to characterize the soil type by classifying it to one of the known soil types. There are different algorithms of object classification in multidimensional spaces [13]. One of the most effective and easy realizable method is the *k-nearest neighbour method*.

This method uses distances from a point of an unknown class to all points belonging to the known

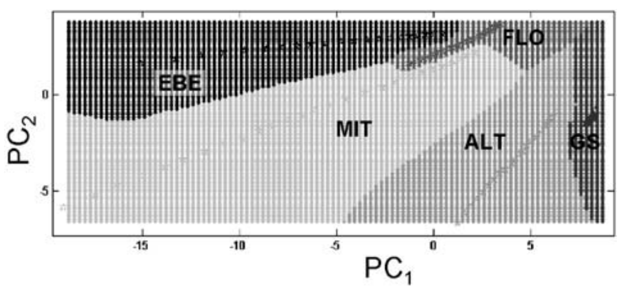

Figure 13: Classification of unknown soil types after PCA using *k-nearest neighbour* method.
Bild 13: Klassifizierung von unbekannten Bodenarten nach HKA mittels *k-nearest-neighbour*-Methode.

classes. The results are sorted and the *k* nearest points (neighbours) are selected. The unknown is classified to the class with the largest number of members in the *k* neighbours. The choice of the parameter *k* depends on the distance between the known classes. If they are mixed or close to each other the *k* should be increased.

This method finds the nearest class, but cannot identify new classes. However, for soil characterization this method is sufficient (Fig. 13), if enough well known soil types were considered.

10 Soil Moisture Measurement for a Classified Soil Type

For soils already classified the impedance measured at one frequency only or the mean value of impedance over the frequency range allows to calculate soil moisture. Figure 14 shows as example the linear dependence of the soil moisture for the soil type ALT from the mean value of the imaginary part of admittance in the range 2 to 35% (vol. moisture). Similar results were obtained for the other soil types. It was observed that the linear dependency was in every case fulfilled in the relevant moisture intervals for agricultural and environmental applications.

The imaginary part of the admittance should be preferred for moisture calculation because of the lower salinity dependence (Table 2) [15].

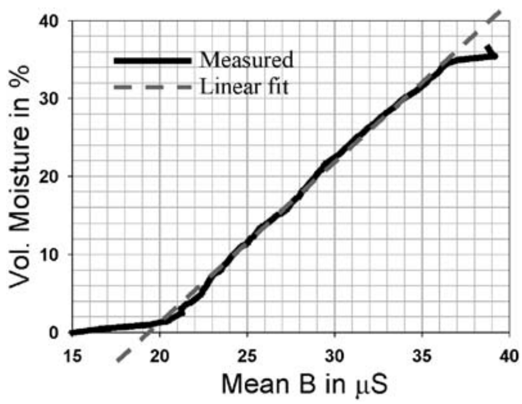

Figure 14: Relation between volumetric soil moisture and the mean value of *B* over frequency range 2 . . . 100 kHz (Soil type ALT as example).
Bild 14: Zusammenhang zwischen volumetrischer Bodenfeuchte und Mittelwert von *B* über dem Frequenzbereich 2 . . . 100 kHz (Bodenart ALT als Beispiel).

Water type relative to salinity	Elect. conductivity in mS/cm	Diel. permittivity (Dielectric constant)
Distilled water	0.05	80.1
Rain water (Salt content ∼ 1 g/L)	5–30	79.9
Plant-specific max. limit for salt saturated soils (Salt content ∼ 3.29 g/L)	∼ 5200	79.3
Seawater (Salt content ∼ 35 g/L)	45 000–55 000	72

Table 2: Effect of water salinity on real and imaginary parts of the admittance [16].
Tabelle 2: Einfluss des Salzgehalts von Wasser auf den Real- und Imaginärteil der Admittanz [16].

As shown in Table 2 the influence of salt content on the imaginary part of admittance is much lower than on the real part. In practice salt content for various soil types changes with time by less than 0.5 g/L. Therefore it can be expected that in this case the imaginary part of the admittance leads to a maximal absolute error of 0.25% volumetric moisture.

11 Conclusion

A new approach for soil moisture measurement based on impedance spectroscopy was presented in this paper. The fundamental concept is to characterize the soil type using extensive laboratory experiments before moisture calculation. The method was developed using a measurement data set corresponding to natural soils with different compositions. The measurements were carried out similarly to the practical conditions of the sensor and at the same soil density. The frequency range for signal processing can be selected using the Kramers–Kronig transform and under consideration of electronic circuits available commercially.

The results described in this paper show that the soil type can well be characterized using Principal Components Analysis (PCA) via Singular Value Decomposition (SVD). In this case the a-priori knowledge used during in-situ measurement consists of the measurement data base collected for various natural soils by the manufacturer. The first two principal components only are sufficient for soil type classification. Although no physical knowledge was applied during signal processing, the results are correlated with soil composition.

After soil type classification, the calculation of soil moisture was realized using the linear dependence between volumetric water content and the mean value of the imaginary part of the admittance, providing accurate results.

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