
K.Y. Foo¹, T. Hao², G. Curioni³, D.N. Chapman⁴, N. Metje⁵ and P.R. Atkins⁶.

1 School of Electronic, Electrical and Computer Engineering, University of Birmingham, U.K.
Email: p.r.atkins@bham.ac.uk
2 School of Civil Engineering, University of Birmingham, U.K.
3 School of Civil Engineering, University of Birmingham, U.K.
4 School of Civil Engineering, University of Birmingham, U.K.
5 School of Civil Engineering, University of Birmingham, U.K.
6 School of Electronic, Electrical and Computer Engineering, University of Birmingham, U.K.
Email: p.r.atkins@bham.ac.uk

ABSTRACT

Non-invasive utility location techniques are vital for maximizing the potential of trenchless technologies, especially within an urban environment. This paper proposes the approach of implementing a knowledge-based system (KBS) for predicting the geophysical properties of the soil by taking into account both the geographical and seasonal variation in soil properties. The key motivation for developing KBS as a prediction methodology is the advantage of being able to gather and integrate both analytical models as well as expert knowledge based upon existing and opportunistic data. The design and implementation of this system are presented as a case study for ground penetrating radar, which is mainly affected by the complex permittivity and electrical conductivity of the soil. Soil electromagnetic semi-empirical models are implemented to obtain an estimate of the complex permittivity using geotechnical properties obtained in laboratory tests or found on a national database. Hydrology models are applied to account for variations in soil water content and the associated impact on permittivity values due to changes in precipitation patterns. Results obtained from a ground penetrating radar test site with a long-term monitoring station installed are also presented, showing agreement between measured data and KBS output, and demonstrating potential for improving the effectiveness of utility surveys.

KEYWORDS

Knowledge-based System; Pipe Location Technologies; Soil Geophysics.

INTRODUCTION

Non-invasive, geophysical sensing techniques play an important role in maximising the effectiveness of trenchless technologies that underpin the installation and maintenance of
buried utilities. Based upon this vital motivation, the Mapping the Underworld project (Metje et al., 2007, Rogers et al., 2008) is currently developing a multi-sensor system for utility mapping, with the aim of offering a step change in detection and location accuracy. The four main sensing technologies in the multi-sensor approach are in-pipe ground penetrating radar (GPR) (Zhang et al., 2010), low-frequency electromagnetic (Foo et al., 2010), seismo-acoustic (Muggleton & Brennan, 2008) and magnetic detection techniques (Wang et al., 2010). While the sensing techniques are crucially important in achieving this objective, it must be noted that the environment in which these utilities are buried influences the performance of the sensors. One known example is the attenuation of electromagnetic signal in conductive soils, which typically explains the shallow penetration depth of GPR on sites that are electrically conductive. In addition, soils that are highly conductive will also pose a problem for passive magnetic sensing as the magnetic fields from targets (primarily live power cables) are attenuated due to the flow of Eddy currents in the ground. Therefore, a better understanding of the ground and its interaction with the geophysical parameters that are measured provides a means for optimising the multi-sensor approach.

While data from available databases provide information on the geographical variation of soil properties, there is little readily available information on the seasonal variation in soil moisture content, a factor that directly affects soil electromagnetic properties (Topp et al., 1980). For example, depending on soil composition, soil moisture content may vary with precipitation patterns for up to 2 metres depth. At sub-zero temperatures, moisture accumulated in the top soil may freeze and this significantly reduces the effect of ionic conductivity. However, in urban areas where most utilities are laid, surface structures such as roads and pavements will alter, and may negate, the effect of precipitation patterns. In such circumstances, the effect of the composition of the surface structure will need to be accounted for, while expert knowledge on the conditions of the surface structure may offer an indication of potential localised soil moisture variation from weather effects due to exposed ground attracting water run-off from adjacent surfaces. Therefore, while a simple prediction model is desirable, the local conditions and circumstances under which surveys will be carried out imply that the set of available input parameters can be unique at each site. The ability to interpret a wide range of available information would require a wide knowledge-base in order to best utilise any available input parameters in order to predict the electromagnetic properties associated with the performance of the sensors. This is the key motivation for implementing a knowledge-based system (KBS) approach for this work.

The aim of this study is to form a link between available or easily obtained knowledge of the ground and its geophysical properties, primarily the electromagnetic (and electrical) properties. In the U.K., the National Geotechnical Properties Database (NGPD) (Self & Entwisle, 2006) holds a large collection of soil geotechnical properties nationwide and is maintained by the British Geological Survey (BGS). There is also a soil properties map maintained by the National Soil Resources Institute that is geared towards agricultural science, providing estimates of soil composition and water retention characteristics. The subsequent sections
describe the implementation of the KBS, followed by a case study based upon a test site with an installed monitoring station.

**KNOWLEDGE-BASED SYSTEM APPROACH**

The concept of applying a knowledge-based system to soil related research can be traced back to the need for computer-aided soil classification (McCraken & Cate, 1986), initially motivated by the large number of rules, inter-parametric associations and subjective evaluations that are involved in the classification of soil for agricultural purposes (Soil Survey Staff, 1975, 1993). Research in this domain then developed on two fronts, building a rule-based inference engine in the form of a computer program (Galbraith et al., 1998), and the application of fuzzy logic in order to obtain a representation of subjective evaluations that can be operated on by means of computer algorithms (Burrough et al., 1992, McBratney & Odeh, 1997, Hu et al., 2003).

While the earlier implementations focussed on automating the rule-based decision making process using inputs of semi-subjective evaluations, this work is primarily motivated by the need to integrate different knowledge domains, along with input from experts, in order to form an informed prediction of the soil conditions associated with a multi-sensor utility location system. The case for such an approach was made for GPR sensing by Rogers et al. (2008). A closely-related approach was documented by Wunderlich et al. (2010), whereby the geophysical attributes of the soil are linked to soil parameters using a set of geophysical transfer functions that are formed by applying predictive models. In comparison, this work is unique in that the KBS approach integrates subjective expert knowledge and observations, such as the type and conditions of the road surfaces and pavements. More importantly, this work considers and accounts for the seasonal variability of soil parameters and its impact, a factor that may not be negligible in the U.K., and possibly other countries, especially for shallow subsurface surveys and in applications where long-term subsurface asset monitoring is required. Fig. 1 shows a block diagram of the KBS, called MTU-KBS.
There are three key inputs to the MTU-KBS: the link between available geotechnical properties of the soil and its electromagnetic properties, the seasonal variation of the soil moisture content, and the input of expert knowledge on the soil, including opportunistic approximation by individual sensors where possible. The main output from the MTU-KBS is the prediction of the geophysical properties associated with individual sensors. This provides an estimate of the suitability of individual sensors to the survey site. Fine-tuning of the sensors can then be carried out locally by the individual sensors, and the fine-tuning of the multi-sensor device as a whole by refining the weighting and confidence of individual data streams applied in the data fusion stage (Chen & Cohn, 2011).

DESIGN AND IMPLEMENTATION

Linking soil geotechnical and geophysical properties. The literature on soil electromagnetic properties presents a number of modelling and prediction methodologies. A comprehensive review is presented in (van Dam et al., 2005). For this work, it is important that the required parameters for any chosen predictive model are available or measurable within an acceptable time-frame. Based upon the availability of a growing national database of geotechnical properties, it is optimal to identify models that can operate on these data. The models that satisfy this requirement are semi-empirical models, in which the complex permittivity of the soil with respect to the frequency of electromagnetic signals can be modelled using inputs of soil composition and water content. Other modelling approaches, such as volumetric modelling, requires rigorous a priori information of soil geophysical
properties in order to arrive at a result, they are more analytical in their formation and application. Semi-empirical models are a set of mathematical equations that link the complex permittivity of soil to its composition and water content, thus offering a predictive capability. These formulations are obtained by studying the electromagnetic properties of a set of soils with varying textures and water content and then deriving a best-fit solution for the observed data. The two well-known semi-empirical models are the Topp model (Topp et al., 1980) and the Peplinski model (Peplinski et al., 1995). The Topp model’s inherent limitation is in dealing with highly electrically conductive materials, including soil with a high clay content. The Peplinski model, widely applied for applications with a frequency range of 0.3 to 1.3 GHz, has been recently updated and expanded by Mironov et al. (2009). The choice of this latter model is desirable given the availability of soil composition data from the NGPD, while soil classification tests are routinely performed on soil samples extracted from surveys being carried out in urban areas. The KBS should, and can, allow modular increase to the choice of modelling methodologies as well as the refinement of integrated models. Therefore, the choice of this semi-empirical model presents a starting point for the implementation of the KBS and does not define its limitation.

The input parameters to the Minorov et al. (2009) model are the composition of clay (<0.002 mm), non-clay content, and water content. If C, f, and w are defined as the percentage of clay content, the frequency of the electromagnetic signal and volumetric water content (VWC) respectively, the model can then be described as

$$\varepsilon = F_D(C, f, w), \text{ where } \varepsilon = \varepsilon' - j\varepsilon''$$ (1)

such that $\varepsilon$ is the complex apparent permittivity, $\varepsilon'$ and $\varepsilon''$ are the real and imaginary components respectively, and $j = \sqrt{-1}$. The function $F_D$ denotes the set of mathematical formulations as detailed in Mironov et al. (2009) that generates a hypothetical value of $\varepsilon$.

The material attenuation loss in dB (the range is accounted for in the expression), $L$, for a GPR can be expressed as (Daniels, 2004):

$$L = 20 \log_{10} \left[ \frac{4 \pi f}{c} \left( \frac{\mu_r \varepsilon_r}{2} \sqrt{(1 + \tan^2 \delta)} - 1 \right) \right]$$ (2)

Where
$R$: distance from the GPR antennas to the target
$f$: frequency in Hz
$c$: speed of light in vacuum
The relative permeability (magnetic) of the soil is usually assumed to be 1 unless there is a rich presence of ferrous or calcite minerals. The attenuation loss, \( L \), is related to the complex permittivity via the loss tangent, such that

\[
\tan \delta \approx \frac{\varepsilon''}{\varepsilon'}
\]

while the electrical conductivity, \( \sigma \), is estimated as

\[
\sigma \approx \varepsilon' \omega \tan \delta
\]

It is worth noting that in applying equation (4), \( \varepsilon_0 \) should be accounted for in \( \varepsilon' \). Equations (1), (3) and (4) establish the link between geotechnical parameters of soil in terms of clay and water content, and the geophysical parameters of complex permittivity and electrical conductivity. Equation (2) demonstrates that the complex permittivity relates to the attenuation loss due to the soil. The electrical conductivity gives an indication of the bulk resistivity of the soil.

**Modelling the effects of seasonal variation.** One of the parameters required for the modelling of bulk soil permittivity and conductivity is the soil VWC. Depending on the type of ground surface on the site under investigation, seasonal weather patterns can affect VWC. Soil hydrology is to a large extent influenced by soil textural characteristics, and an empirical model was developed by Saxton and Rawls (2006) to predict soil water characteristics using soil textural information. If \( S, D \) and \( OM \) represent the percentage of silt, sand and organic matter in the soil, and \( \rho \) its bulk density, then

\[
[\theta, K] = F_w (D, S, C, OM, \rho)
\]

in which \( F_w \) denotes the empirical model as detailed by Saxton and Rawls (2006), providing an estimate of the saturated water content, \( \theta \), and the hydraulic conductivity, \( K \), which are then used to estimate the change in water content at various depth after a rainfall event.

**Expert knowledge and approximation.** The system also allows the user to input expert knowledge or potentially useful information based upon subjective experience. In order to extract and use relevant information, a question-tree is designed for each subject of interest. The question-tree and underpinning logic may be formed by a combination of documented knowledge as well as by the informed opinion of a large sample of practitioners. The template governing the question-trees is shown in Fig. 2.
Each set of options is unique to a question, and has an associateable and discernible impact on the parameter of interest. The various combinations of options from each question block can be mapped to a numerical value, or grouped together to form another subjective evaluation, but the key is that these interpretations and their impact on the parameter of interest must be pre-defined along with each question block. The task of selecting answers to the question blocks can also be accomplished by deriving answers from other sources if available.

CASE-STUDY ON TEST SITE

Test site. A case-study is herein presented to demonstrate the KBS approach. This is based upon a test-site on the University of Birmingham campus with a long-term time-domain reflectometry (TDR) monitoring station (Curioni et al., 2010) installed, as shown in Fig. 3. TDR measurements from probes positioned at various depths below the ground surface were obtained at regular time intervals. The values used in this paper were obtained at a depth of 0.6 m below the ground surface. The surface of the site is covered with grass.
Laboratory and in-situ measurement. In order to characterise the soil, a soil sample at similar depth was obtained and a grading test was performed in the laboratory to obtain the particle size distribution. The result is shown in Fig. 4. The grading test results provide a soil composition of approximately 2% clay, 3% silt and 95% sand. The complex permittivity of the soil was also measured in situ using an open-ended coaxial probe and a vector network analyser, producing the frequency-dependent complex permittivity as shown in Figs. 5 and 6. It was observed that the complex permittivity is reasonably consistent across the frequency range of 100 to 800 MHz (a typical frequency range for subsurface surveying GPR), exhibiting only very small dispersion.
Figure 5. In-situ characterisation using an open-ended coaxial probe and a vector network analyser.

Figure 6. Complex permittivity of the soil measured in situ using an open-ended coaxial probe, demonstrating very small dispersion between 100 to 800 MHz.

Modelling with MTU-KBS. A period of 64 days between Oct and Dec 2010 was chosen. The initial volumetric water content (on Day 1) was estimated as 19%, using TDR measurement from a day when the last rainfall event was more than 3 days before. The organic matter content was approximately 3% in order to account for the grass surface. The soil composition data and the initial VWC estimate were input to the KBS, applying eqn. (5), in order to model the variation of soil water content using rainfall data collected from a weather station less than 100 m away. The estimated variation of VWC within this period
and the soil composition data measured with grading tests were then applied to eqn. (1) in order to generate the variation of soil complex permittivity. The frequency was set at 250 MHz as a required input parameter, but the actual value, as long as it is within the range of 100 to 800 MHz, should have no major impact as the soil is relatively non-dispersive (as seen in Fig. 6). The results obtained using the MTU-KBS are shown in Fig. 7. The apparent permittivity is estimated by taking the modulus of the complex permittivity.

Figure 7. MTU-KBS modelled variation of apparent permittivity plotted against rainfall data for the test site between Oct to Dec 2010 at 0.6 m depth.
By comparing the results in Figs. 7 and 8, it may be observed that there is a good match between the modelled and measured variation of apparent permittivity over the 64-day period. The correlation between rainfall events and the change in permittivity are observed in both the modelled and measured results. The mean difference between the modelled result and the measured values is 0.66. The variation between the minimum and maximum permittivity after the main rainfall event (as indicated in Fig. 8) is a 12% increase modelled by the MTU-KBS as compared to a 17% increase measured by the TDR monitoring station.

Optimising GPR. In order to demonstrate the impact of seasonal variation on pipe location technologies, a GPR was deployed for surveying a pipe buried at a known depth of 0.5 m from the ground surface. This pipe was buried approximately 2 m away from the monitoring station, covered with the same grass surface and is known to have a similar soil profile. The surveys were conducted on a pre-determined and fixed line on the ground surface to ensure spatial consistency. The processed GPR data shown in Fig. 10 gives a comparison of the GPR survey obtained before and soon after the main rainfall event.
The surveys indicate that the attenuation losses are negligible as strong hyperbolae are seen in both cases. This conforms well to the expectation as the soil is predominantly sandy. However, on closer inspection, it is possible to notice a change in the shape of the hyperbolae, such that the arms of the hyperbolae in wet conditions are seen to have a smaller angle. In addition, the vertical distance (depth) between the two strongest hyperbolae is slightly larger in the wet conditions. Both these symptoms point to a slower speed of signal propagation (and hence the perception of larger distance), implying a higher bulk permittivity. A total of 5 surveys were conducted in each condition, and these symptomatic differences between dry and wet conditions were consistently observed. In order to quantify this difference, Fig. 11 presents a plot of the GPR signal return corresponding to the hyperbola near the 175\textsuperscript{th} distance index, for both the dry and wet conditions. In both cases, the distance index slice that has the smallest depth index to the peak of the hyperbola (the shortest range of approach to the hyperbola) was selected.

Figure 11. Delayed GPR signal in dry versus wet conditions, as observed at depth indices where a buried pipe is known to be present.
The difference can now be calculated as an increment of \(\frac{5}{92}\) percent in terms of depth index (or the number of range cells), equivalent to 5.4%, and resulting in an average increment factor of 1.054 in terms of depth. Given that the signal propagation speed \(\propto \frac{1}{\sqrt{\varepsilon_r}}\), and that the sampling frequency of the radar’s analogue-to-digital converter remains unchanged, it is then calculated that the permittivity had varied by a factor of 1.111, equivalent to an increase of 11.1%. This result is comparable to the 12% increase predicted by the MTU-KBS and 17% increase measured by the TDR. The smaller increase in apparent permittivity observed with the GPR is likely to be due to the fact that the time and day of the GPR surveys did not correspond exactly to the time that the minimum and maximum permittivity values were observed, which of course, can only be determined after the TDR and weather station data were collected and processed.

This demonstrated that seasonal variation can have a significant impact on the accuracy of utility depth information, especially in exposed ground and at shallow depths. Although hyperbolic processing can be used to predict actual permittivity, this is dependent on the presence of strong target reflections that may prove elusive in more attenuative soil conditions. The ability of the MTU-KBS to predict the complex permittivity of the soil, while accounting for seasonal variation, is therefore an effective approach especially in complementing GPR processing techniques. As in this case study, if one has the ability to predict that the permittivity values will increase by approximately 12% due to a recent weather event before a survey is carried out, it can then be decided if the day is suitable for a survey, and subsequently, any GPR data collected on the day can be appropriately compensated. Furthermore, the multi-sensor data fusion algorithms would recognise that the data collected on the day will reflect a higher permittivity as compared to the same set of data collected on a drier day. Without such information, and in the absence of strong target returns, data fusion algorithms would have little a priori knowledge to rely upon in dealing with the variation in GPR data.

CONCLUSION

This study presented the motivation, viability and practical advantages of a KBS system for evaluating soil geophysical parameters that impact upon pipe location technologies, while proposing the foundation structure of this system. Semi-empirical models employed in the MTU-KBS are based upon soil attributes that are widely available. The approach is unique in that both spatial and seasonal variations of soil attributes are accounted for in the modelling of soil geophysical parameters, while allowing for expert input using a structure and pre-designed question-trees.

In the case-study based upon a test-site on campus at the University of Birmingham, both the soil composition and electromagnetic properties were identified using laboratory and in-situ
measurements. Using the developed MTU-KBS, the variation in soil water content was first predicted using weather station data, and then applied to produce a complex permittivity variation model. This was then compared to data measured using a long-term TDR monitoring station, showing good agreement with a mean difference of 0.66. A GPR was deployed over a known buried target on the test site in order to assess the impact of seasonal variation, demonstrating that a pipe buried at a depth of 1 m can appear to be up to 5% deeper if the rainfall during the observation period of this case study was not accounted for.

As with most models, the models applied within the MTU-KBS are inherently an imperfect representation of real events and physical conditions. Therefore, while a very accurate prediction may not always be feasible, it is worth noting that the aim of implementing this approach is to provide an effective means by which any relevant information, including those being made available for the future, can be applied and integrated to evolve the system for the purpose of optimising the planning, interpretation and fusion of buried utility surveys.

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