Geotechnology: Paradigm Shifts In The Information Age

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Abstract
Startling advances in microelectronics, sensors, computer power, communications, digital data analysis, data storage and visualization have been taking place during the last decades. Geotechnology is prepared to gain maximum benefit from the information revolution. Embracing information technology will trigger important changes in the way we teach, learn, investigate, conduct field studies, design and construct systems. New solutions cannot circumvent the fundamental physical, chemical and biological laws that govern the behavior of geomaterials. In this time of changes, we need our best engineering skills and ingenuity to explore new problem solving strategies.

Introduction

The optical characteristics of lenses, well recognized in the 13th century, led to two important inventions and respective scientific revolutions. The telescope allowed Galileo Galilei (Italy, 1564-1642; 30 magnification) to see moons orbiting around Jupiter and led him to challenge the pre-Copernican view that the Earth was at the center of the universe; this started a revolution in astronomy. On the other hand, the microscope allowed Anton van Leeuwenhoek (Holland, 1632-1723; 270 magnification) to see bacteria for the first time: this started the biology revolution. More recently, the development of tunneling microscopy and atomic force microscopy in the 1980's set off the nano-technology revolution, which had been anticipated by R. Feynman in 1959. These examples suggest that the development of new technology has often prompted important changes in theories, goals, practices and expectations in technological and scientific communities. These are "paradigm shifts".

The development of geotechnical engineering has benefited from scientific and technological innovations in related fields such as mechanics, fluids, chemistry, physics, computers and numerical methods (and we already anticipate the influence of biology). In this context, one must wonder about the potential impact and associated paradigm shifts that the ongoing information technology revolution can have in geotechnical engineering.

This manuscript starts with historical highlights in the evolution of information technology, includes an analysis of the various areas that sustain the exponential growth of information technology, speculates on possible paradigm shifts, and explores the human side of the information age. While related topics are extensively discussed elsewhere, the purpose of this review is to create a platform from which we can explore the horizons of our field in the information age.

Areas that Sustain the Information Revolution

Information technology combines various fields, such as microelectronics, computers, sensors, data storage and display, digital data analysis (signal processing and inverse problem solving), numerical methods, and communications (cellular telephony and the internet). Their interwoven history is summarized in Table 1. A cursory review of these historical developments reveals the mutual synergism between these parallel fields. Salient observations follow.

Exponential Growth in Microelectronics
The invention of the transistor in 1947 marks the beginning of microelectronics. Fast early growth lead to the 'bizarre' prediction by 1965, that the number of transistors per chip would double every 18 to 24 months (known as Moore's Law, yet modified from Moore's original paper – Stokes 2003). This prediction has been amazingly sustained since (Figure 1). Today's research looks into 3D rather than 2D packing (speed is controlled by internal length scale), nanofabrication, alternative materials, photonics, and the quantum physical limits among others.

Table 1. The interwoven history of fields the sustain the information revolution

Year	Event
Before 1900	J. Napier works on calculation algorithms. Mechanical calculators are invented by W. Schickard (1592-1635), B. Pascal (1623-1662 - add and subtract), and G. Leibniz (1646-1716 - multiply and divide). G. Boole (1815-1864) explored automatic reasoning leading to "boolean algebra". Maxwell (1831-1879) publishes his treatise on electromagnetism in 1873. H. Hollerith (1860-1929) invents electronic counting for the 1890 US census; he later founds IBM.
1910's	I. Fredholm introduces the concept of the generalized inverse for an integral operator (1903).
1920's	E.H. Moore presents the generalized inverse of matrices (1920). The field of consumer electronics starts with the sale of radios and electronic phonographs.
1930's	Car radios and portable radios become common.
1940's	The first digital computer is built by H.H. Aiken (1944). The transistor is invented at Bell Labs (1947 – Nobel Prize: J. Bardeen, W. Brattain, and W. Shockley). Digital signal processing starts. Correlation techniques are developed to recover weak signals in the presence of noise. The Singleton's digital correlator rapidly performs storage, multiplication, and integration by a binary digital process (1949). *Publication of "Soil Mechanics in Engineering Practice" by Terzaghi and Peck in 1948.*
1950's	Sony develops the pocket-size transistor radio. Shannon theorizes that a message can be encoded and transmitted in "bits" (1956). The Dartmouth Conference on artificial intelligence takes place (1956). Integrated circuits start at Texas Instruments (1958). The Si-pressure microsensor is first commercialized in 1958. R. Feynman recognizes the potential for developments at the molecular scale and anticipates nano-technology (1959).
1960's	Computers emerge. Beginning of surface micromachining. Integrated circuits lead to new and improved technologies and consumer products. There is rapid growth in the new field of digital signal processing and it begins affecting consumer electronics related to voice, music and images. J. Tukey and J. Cooley introduce the Fast Fourier Transform algorithm (1965). *Constitutive modeling and numerical simulations begin in geotechnology.*
1970's	Microprocessors are developed (1971) and the size of computers decreases to a chip. The power of integrated circuits starts doubling every 2-3 years. Consumer electronics begin their transition to digital. A.M. Cormack and G. Hounsfield receive the noble prize for computerized tomography in 1979. Rapid development of alternative transducers, e.g., silicon based.
1980's	Personal computers reach homes. CD players are introduced in 1982. Record players vanish from the market in less than a decade. Texas Instrument brings single-chip digital signal processor into mass production. Commercial cellular phone service starts. Fast growth of micromachining, initially using selective etching techniques. Various forms of microactuators are developed.
1990's	Very few analog consumer electronics remain in the market. There is a rapid growth in digital memory and storage capabilities. IBM Deep Blue defeats G. Kasparov (1997 - processing speed of ~40 Tera operations/sec). Bio-MEMS are developed. We gain almost instantaneous access to vast information through the world wide web.
2000's	Submicron electronic devices are readily available. There is rapid increase in nano-technology and more than 30 nano-technology research centers operate in the US.

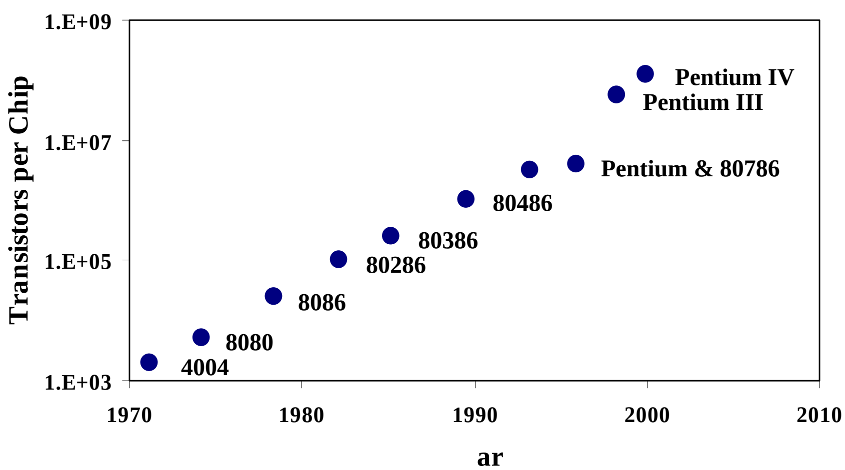


Figure 1. Microelectronics: The evolution of the transistor – Moore's Law
(data from J. Birnbaum 1997 in URL: www.acm.org; and A. Akinwande in URL: ocw.mit.edu)

Micro-electrical mechanical systems MEMS is a subset of microelectronics dedicated to the development of sensors (e.g., vibration, pressure, temperature, chemical) and actuators (e.g., motors and micro-mirrors). Typically, the sensing element or the micro-actuator and the corresponding electronics sit on a single substrate. Challenges in MEMS technology include capability of self-regulation, wireless communication, low power operation, and heat dissipation. Optical MEMS (e.g., diffraction gratings, optical sensors, and micro-mirror arrays) and bio-MEMS (combination of MEMS sensors and actuators) promise important future developments.

Exponential Growth in Sensors – Data Generation

Sensors assess state or change in state in the system under investigation through mechanical, thermal, electrical, magnetic, photonic or bio/chemical energy, and provide an output signal that is either in terms of current or voltage. Analog sensors produce a continuous signal (which may be digitized before or after transmission), while digital sensors produce a digital output or logic levels. The response of the sensing element may be monitored through a resonant system and encoded in the output frequency (e.g., resonant micro-sensors MEMS and geotechnical vibrating wire instruments). Frequency and digital encoding prevent signal corruption and deterioration during transmission. A wide range of fiber optic sensors are based on sensing units that are monitored by light reflection, interferometry or diffraction; optical systems are immune to electromagnetic interference and are robust for chemical and environmental applications (TDR: O'Connor and Dowding 1999; sensors in series: Pamukcu et al, 2005a&b; point sensor: URL: www.fiso.com).

Sensors have experienced important changes in the last decades; the case of pressure transducers is explored in Table 2 (the comparison can be extended to include range, precision, durability, installation difficulties and cost). This example highlights major changes in the sensing method, transduction, data transmission and size.

Table 2. Evolution in sensors – The case of pressure transducers

Period	Sensing unit	Transducer	Transmission	Size
Early 1900's	open standpipe piezometer	measuring tape	fluid-based	m
	pneumatic piezometer	pressure gauge		dm
Mid 1900's	elastic membrane/diaphragm	strain gauge vibrating wire	wire-based	several cm
Late 1900's	MEM sensor elastic membrane/diaphragm	capacitance or resonance	wireless (possible)	sub cm
	silicon diaphragm	light interferometry	fiber optic	$< 10^{-3}$ m

Current research in sensors and sensing systems includes issues related to miniaturization into micro and nano-sensors without sacrificing range and precision (Figure 2), distributed sensors and sensor networks (including optimal sensor location), inter-sensor wireless communication, embedded systems, intelligent sensor systems (i.e., provide new information e.g., through signal analysis), distributed processing, and optimal data analysis such as signal processing within the framework of arrays (Glaser 2004; Glaser et al. 2005). Given the market needs and resources, we should expect important additional developments in chemical and biochemical micro sensor systems.

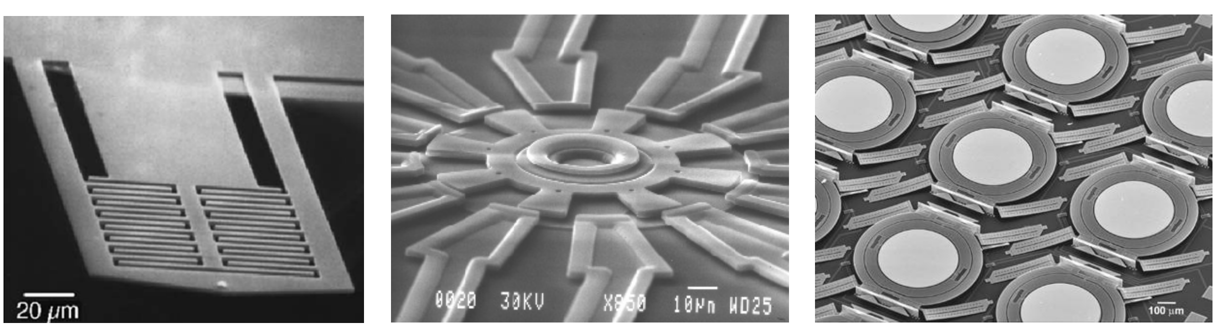


Figure 2. MEMS (1) Cantilever displacement sensor - Yaralioglu et al. 1998. (2) Motor - U. Colorado Boulder mems.colorado.edu. (3) Micro-mirror array (Bell Labs, URL: www.bell-labs.com/news/1999/)

Exponential Growth in Computers – Data Processing and Storage

The exponential growth in computer power and storage together with the exponential decrease in cost (and size) is captured in the two plots in Figure 3. Current computer capabilities exceed 10^4 TB (Note: 1 bit stores either 0 or 1, one byte= 8 bits, one terabyte TB=1024^4bytes=8.8×10^{12}bits), and a speed of 10^4 MIPS (MIPS= million instructions per second).

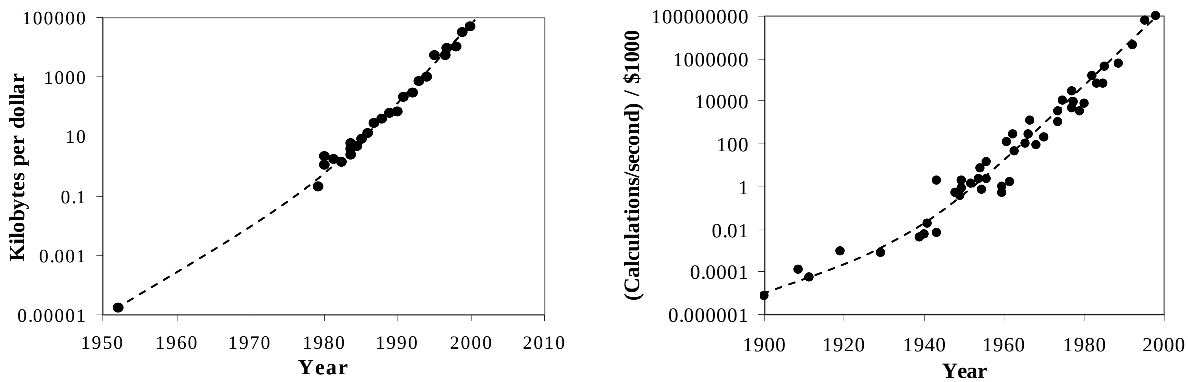


Figure 3. Evolution in Computer Capabilities (data from Kurzweil 2001)

These numbers are best comprehended in the context of the human brain capacity. Various hypotheses lead to quite different estimates of the brain storage capacity. Consider the average brain size 1.4 liter, neuron size 2μm and effective molecular size for short chains 20Å; then: (1) if each neuron stores 1 bit, the brain storage capacity is ~20 TB; (2) if storage is determined by synapses among neurons, then assuming 10 synapses per neuron gives a brain storage capacity of 200 TB; and (3) if storage takes place at the molecular level, then the brain storage capacity could be in the order of 2.10^{10} TB. In addition to great storage, the brain can perform a large number of operations per second (a rough estimate suggests 10^8 MIPS). While the human brain power still exceeds computer power, extrapolations of the current rate of exponential growth suggest a crossing point within one or two decades (Moravec 1998).

Exponential Growth in Communications – Data Transfer

The revolution in communications has coincided with and benefited from concurrent changes in digital technology, electronics, optics, and wireless systems, including fairly recent developments in satellite-based communication, cell telephony and the internet. Changes in the rate of information transfer and cost are captured in Figure 4.

The communication revolution has altered a large number of well known everyday activities, including home security monitoring, home detection monitoring systems, vehicle tracking systems, and monitoring systems for the elderly. The same technology can be readily used to affect all aspects of engineering practice, including the possibility of implementing design and monitoring from remote locations, anywhere in the world.

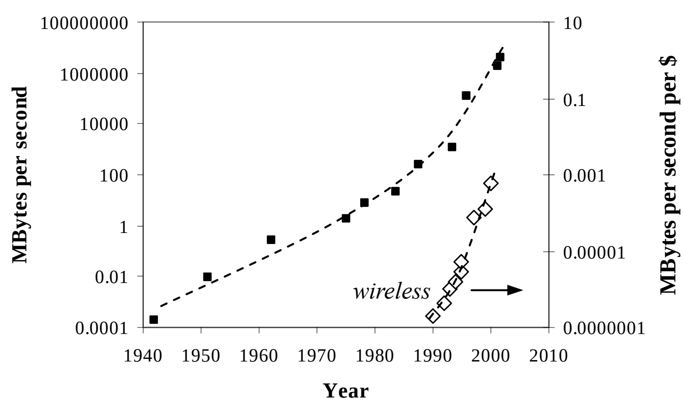


Figure 4. Revolution in Communication Capabilities (data from Kurzweil 2001)

Extracting Information from Data

Inexpensive sensors, extensive databases, and efficient communications have lead to unprecedented access to data. In turn, this has triggered research on varied fields such as data storage and compression, display, data mining, data fusion, information quality and uncertainty, information/feature extraction, in-line decision making, and decision support systems. Common information extraction procedures are introduced next; implications in geotechnology are discussed in the following section.

Analysis of Databases

Databases permit the identification of cause-effect relationships and testing hypotheses about the behavior of materials and systems. The conception of the periodic table is a wonderful example: D. Mendeleev (1834-1907) compiled the limited information that was available about the few known elements in the 1860's and arranged cards 'spatially' on a table as he considered various logical sequences; in so doing, he recognized the several chemical groups, predicted missing elements, and even identified incorrect data.

The potential benefits of extensive databases gains relevance in complex systems where causal relations defy simple, logical tracking, such as in medical diagnosis and therapy. The development of extensive databases has allowed the medical profession to identify the most important cause-effect relationships between our health and our genes, food and lifestyle. The impact can be astounding.

Consider the diagnosis of heart failure for patients walking into emergency rooms. All the evidence shows very high variability among professionals and institutions. Goldman et al. (1996) studied a database of 10,682 patients with acute chest pain at seven hospitals between 1984 and 1986 and identified that only four clinical features are sufficient to assess the risk of heart complications: Q waves in electrocardiograms, low systolic blood pressure, abnormal respiratory sound with fine crackles, and exacerbation of known reduced blood flow to the heart. By evaluating only these 4 symptoms, medical doctors can avoid misdiagnosing critical cases, expedite admission and treatment when necessary, and prevent costly stays in intensive care when unnecessary. Furthermore, this result provides important clues for cause-symptom association that can guide further research into heart failure.

Discrete Signal Processing

A signal is encoded information. The record of water elevation in Southwest Louisiana during the summer months of 2005 is shown in Figure 5: (1) The one-day period is caused by the daily rotation of the Earth and the gravitational pull of the Moon on ocean waters. (2) The fourteen-day long fish-like oscillation in amplitude is a beat function, therefore, there must be at least two underlying events of different frequency – in fact, there are more than 19 harmonic tidal components! The alignment of the Sun and the Moon causes the maximum-high and minimum-low tides for the New Moon and the opposite for the Full Moon. (3) The highest peaks repeat every twenty eight days when the moon completes its cycle - partially seen between days 19 and 47 in this record. (4) Finally, the signal shows that the rhythm described above is perturbed in at least four occasions by named storms and major hurricanes. Clearly, the signal is rich in information!

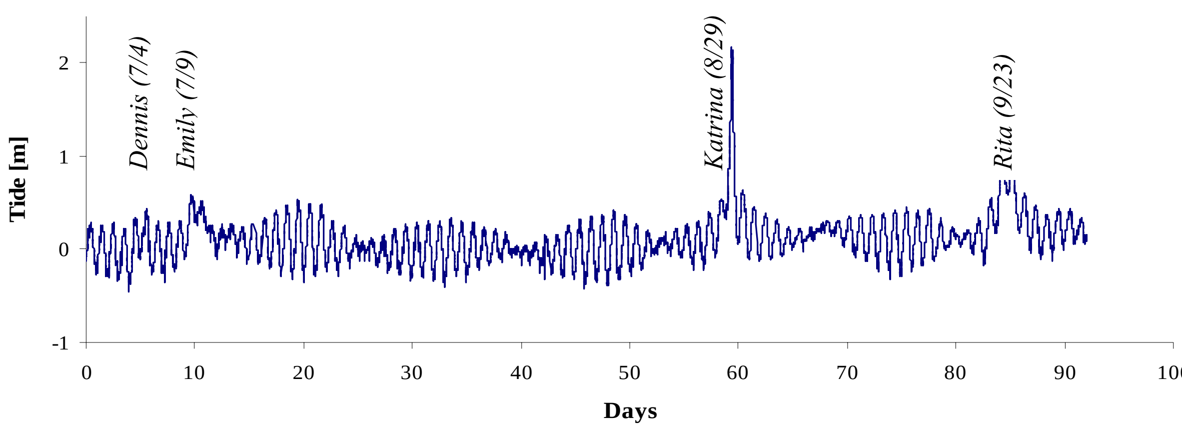


Figure 5. A signal = Encoded information. Data from Pilots Station, Louisiana – NOAA. (from July 1 through September 30, 2005. Average sampling interval: 6.7 min)

Simple and versatile algorithms for discrete signal processing permit operating with noisy signals, identifying similarities between signals, and extracting the characteristics of the system under analysis. Often, these operations can be implemented either in the time domain or after curve fitting the signal with a Fourier series (i.e., computing the Fourier transform). Simple procedures may suffice; for example, signal stacking is a robust approach for noise control (Figure 6 – feature extraction from noisy signals always attempts to cancel noise by averaging in either time or frequency domains). In other situations, more complex analyses are required, such as a 2D Fourier transform of time-varying surface vibration data to infer subsurface characteristics. As data are discrete in space and time, we must be cautious to design experiments that prevent spatial and temporal aliasing.

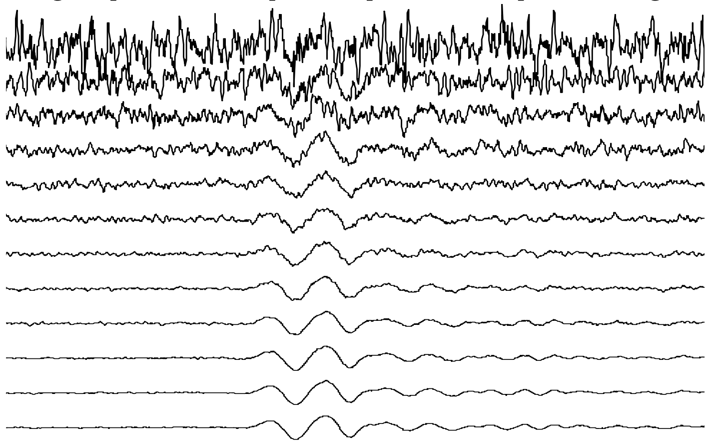


Figure 6. Digital signal processing – Information may be recovered even when the signal is buried in noise (Monitoring bio-gas generation in saturated sand - Courtesy of V. Rebata-Landa)

Data Fusion

Properly "combined" data gathered with multiple sensors can enhance our ability to characterize and comprehend the system under study (Hall and Llinas 2001). We can recognize the different types of data fusion from our daily experience. Our fingers provide same-mode, commensurate yet independent and time-varying tactile input about a surface (e.g., blind person reading Braille). On the other hand, our eyes and ears produce multi-mode, non-commensurate, independent and complementary input (e.g., bat seeking prey). In both cases, our cognitive abilities combine or "fuse" all available data to enhance our comprehension of our surroundings, which in turn improves our ability to select proper actions as we navigate within our context.

Following this analogy, data-fusion (1) combines data from multiple-sensors, multi-modal sensors, spatially distributed sensors, as well as concurrent or time-shifted data streams to extract the needed information with minimal ambiguity; and (2) it may also include decision making and action selection within the network.

Inverse Problems

Experimental data may require inversion to determine the value of sought, unmeasured quantities. Consider the case of a hose connected to a reservoir: the time-varying flow rate coming out of the hose q(t) is directly related to the depth-variation cross-sectional area of the reservoir A(z). Inferring the shape of the reservoir A as a function of depth z from the flow rate signal q as a function of time t is an inverse problem. Inverse problems are ubiquitous in data processing. A few examples in geotechnical engineering are listed in Table 3.

Table 3. Examples of inverse problems in geotechnical engineering

Measured Values	Sought Values
force and deformation data gathered during a triaxial test	constitutive parameters
time-varying pore pressure in an oedometer	coefficient of consolidation, hydraulic conduct.
pollutant concentration in the subsurface	location and timing of leak
geophysical data, e.g., cross-hole times or V_R spectrum	tomographic image, or $V_s(z)$ from SASW (1)
time-varying building settlement	coef. consolidation, secondary compression
deformation data along a pile	stress-strain soil parameters along the pile
earthquake induced ground vibration	evolution of stiffness and attenuation(2)
pore pressure in observation wells	spatial variability of permeability(3)

References: (1) Stokoe et al., 1994; (2) Glaser and Baise 2000; (3) Grimstad et al 2003.

Inverse problems face several difficulties. Consider the example analyzed in Table 4: a stack of particles rests on an instrumented base that permits measuring the force M_i carried by each of the 'm' base particles. The goal is to infer the 'n' applied forces A_j from the m-measured forces M_i. Mathematically, the m-discrete measured values are stored in an array $\underline{M}=(M_1, M_2, \ldots M_j, \ldots M_m)$. Similarly, the n-discrete sought values are stored in an array $\underline{A}=(A_1, A_2, \ldots A_i, \ldots A_n)$. In order to solve the problem, we must select a model that relates measured values $\underline{M}$ and the unknown values $\underline{A}$. This model is captured in the matrix of influence coefficients $\underline{\underline{T}}$ [mxn] so that $\underline{M}=\underline{\underline{T}}.\underline{A}$. The sought values $\underline{A}$ are recovered by inverting $\underline{\underline{T}}$. If the system is overdetermined m>n, the least-squares solution is

$$\underline{A} = \left(\underline{\underline{T}}^T \underline{\underline{T}}\right)^{-1} \underline{\underline{T}}^T \cdot \underline{M}$$

However, most problems are underdetermined and the inversion of $\underline{\underline{T}}$ is ill-conditioned. Then, we either provide more data (e.g., by conducting additional measurements), or request less information from the system.

Table 4: Information in Inverse Problems

Problem: Forces A_j are applied on top of a stack of spherical particles. Forces M_i are measured at the bottom row. Can the intensity and distribution of the applied forces be inferred from the measured forces?

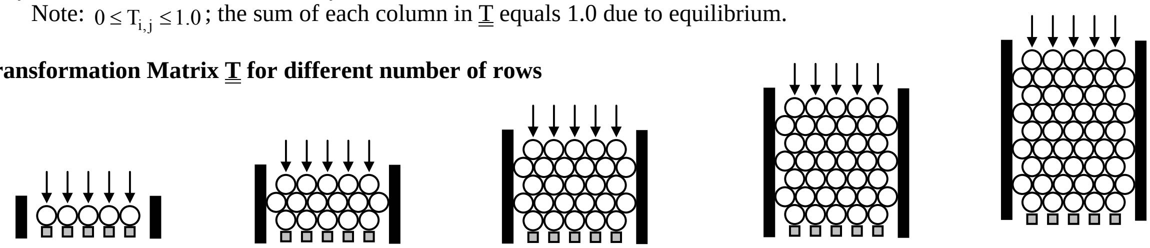
Assumed physical model for load redistribution within the packing:
- a particle on two particles: each particle takes ½ of the load
- boundary particle: the lower particle takes all the load

Constraint on the solution: Equilibrium requires that the sum of inferred forces A_j is equal to the sum of measured forces M_j (assumes frictionless boundaries and vertical forces)

Notation: The system of equations is $\underline{M}=\underline{\underline{T}}.\underline{A}$

M_i: measured force carried by i-th bottom particle M_i
A_j: unknown applied force on j-th top particle A_j
$T_{i,j}$: part of the j-th applied force A_j carried by the i-th base particle M_i
Note: $0 \le T_{i,j} \le 1.0$; the sum of each column in $\underline{\underline{T}}$ equals 1.0 due to equilibrium.

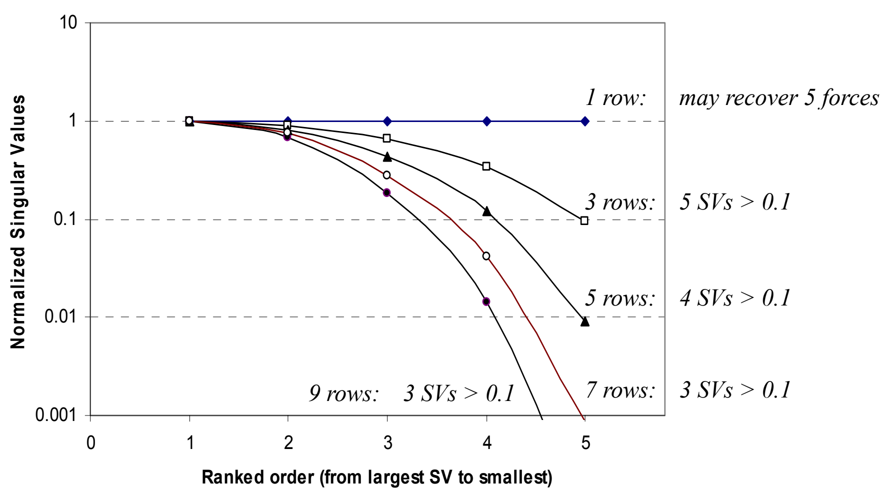
Transformation Matrix $\underline{\underline{T}}$ for different number of rows



$$\begin{bmatrix} 1&0&0&0&0\\ 0&1&0&0&0\\ 0&0&1&0&0\\ 0&0&0&1&0\\ 0&0&0&0&1 \end{bmatrix} \quad \begin{bmatrix} 3&1&0&0&0\\ 1&2&1&0&0\\ 0&1&2&1&0\\ 0&0&1&2&1\\ 0&0&0&1&3 \end{bmatrix}\frac{1}{2^2} \quad \begin{bmatrix} 10&5&1&0&0\\ 5&6&4&1&0\\ 1&4&6&4&1\\ 0&1&4&6&5\\ 0&0&1&5&10 \end{bmatrix}\frac{1}{2^4} \quad \begin{bmatrix} 35&21&7&1&0\\ 21&21&15&6&1\\ 7&15&20&15&7\\ 1&6&15&21&21\\ 0&1&7&21&35 \end{bmatrix}\frac{1}{2^6} \quad \begin{bmatrix} 126&84&36&9&1\\ 84&78&57&28&9\\ 36&57&70&57&36\\ 9&28&57&78&84\\ 1&9&36&84&126 \end{bmatrix}\frac{1}{2^8}$$

Trace= 5 Trace= 3 Trace= 2.4 Trace= 2.1 Trace= 1.9

Singular values SV of $\underline{\underline{T}}$



Several lessons common to all inverse problems immediately follow from the example in Table 4 (see also Santamarina and Fratta 2005):

- *We cannot get more information 'n' than the amount of gathered data 'm'* (additional force sensors could be installed on the sides of the stack in this example). Note that we usually request more information than we actually need; hence, we may often reduce the number of sought parameters 'n'.
- In general, *the further the distance between cause-and-effect, the lower the information that can be gained about the cause from the measured effects*. As the number of particle layers increases, measured forces at the base of the granular pile become correlated, $\underline{\underline{T}}$ becomes less diagonal, the trace of $\underline{\underline{T}}$ decreases, the number of "large" singular values in $\underline{\underline{T}}$ decreases, and the amount of information that can be recovered from the m-measurements decreases.
- As a corollary, do not assume that lots of data means lots of information. *A significant portion of the gathered data is repetitive or interrelated and does not contribute to the information pool.*
- A model must be assumed to relate measurements and sought values. *Select an adequate physical model that properly captures all essential aspects of the problem*. Following Ockham's criterion, *favor simple models* (Jefferys and Berger, 1992).
- Small diagonal elements in $\underline{\underline{T}}$ (or small singular values) invert into large factors that magnify errors when computing the sought values $\underline{A}$. In fact, *errors in the measurements and in the physical model selected to compute $\underline{\underline{T}}$ are propagated and magnified during the inversion.*
- *Pay close attention to experimental design*. The viability of a solution is determined at this stage (rather than by the accuracy of data gathered later).
- The analysis of the matrix $\underline{\underline{T}}$ can diagnose potential inversion difficulties before the experiment is performed. Therefore, *careful analysis of the model matrix $\underline{\underline{T}}$ permits designing laboratory experiments and field instrumentation programs to gain maximum information with the least number of measurements* (includes optimal sensor distribution patterns - e.g., Curtis 2004 a&b).

In the context of geotechnonlogy, the analysis of $\underline{\underline{T}}$ and its invertibility for alternative sensor networks is the mathematical equivalent of engineering guidelines for the design of monitoring programs (listed for example in Dunnicliff 1988).

The previous discussion highlights that the successful solution of inverse problems is strongly dependent on the engineer in charge of designing the experiment and processing the data. In the past, we have designed experiments guided mostly by physical insight. This brief analysis suggests that the design of experiments and the associated instrumentation program must be conceived within the framework of inverse problem solving in view of the information being sought. This observation applies both to field applications as well as laboratory studies (indeed, it is an insightful exercise to analyze constitutive models and their calibration in this light). Readily available and versatile numerical simulators complemented with tools and concepts in inverse problem solving facilitate this task.

Possible Geotechnical Paradigm Shifts

Exciting potential paradigm shifts may take place in geotechnology as we move further into the information age. A few examples in analytical/conceptual, laboratory and field activities are contemplated next.

From "Databases" $\xrightarrow{\text{to}}$ *"New understanding"*

Our field has multiple excellent examples of data compilation and analysis that range from soil behavior (Kulhawy and Mayne 1990) to shallow and deep foundation performance (FHWA - Automated Geotechnical Information and Design System AGIDIS, URL: www.tfhrc.gov/structur/agids/agids.htm). The collection and proper display of spatially distributed local, regional or global information through geographic information systems GIS complemented with built-in analysis tools is another example in this category (e.g., the early USGS index maps; current systems Parsons and Frost 2002; available applications such as the GIS for the city of Paris URL: www.brgm.fr). The availability of such databases and associated tools is already impacting all aspects of engineering, from feasibility studies, planning of site investigation, and design, to hazard analyses.

The probability of extracting proper relations increases as databases become more complete. For example, the correlation between the minimum and maximum void ratios e_{min} and e_{max} of sands and their uniformity coefficient C_u is poor. However, the true role of the coefficient of uniformity becomes apparent when particle roundness R is captured in the database (Figure 7). Similar observations can be extended to the interpretation of penetration resistance when additional data are considered (e.g., shaft resistance, pore pressure), or for settlement estimation in shallow foundations in terms of penetration resistance when complementary shear wave velocity data V_s are incorporated in the database. More complex situations require a data space higher than 3D.

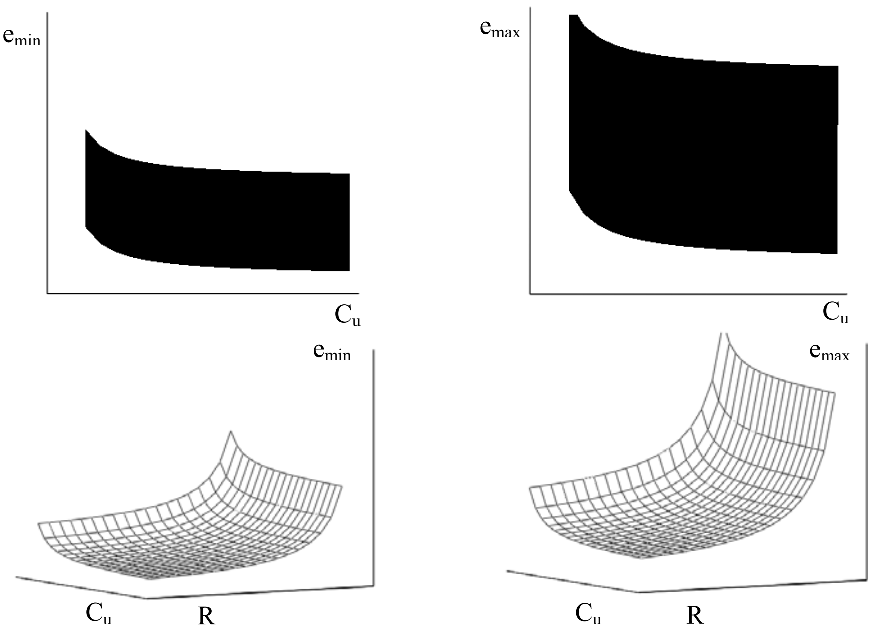


Figure 7. Feature extraction from databases – Lack of correlation does not imply lack of causality
Plots generated using expressions in Youd (1973) – Ranges shown: e=[0,2], Cu=[0,10], R=[0,1]

These examples tell us that *lack of correlation, does not imply lack of causality*; one or more important dimensions may be missing (Figure 7). Conversely, *correlation does not imply causality*; therefore, one should expect important deviations from trends that correlate parameters that are not causally related (e.g., lightly cemented sands falsify G_{max} and q_c correlations). Combinatorial test design and high throughput testing capabilities facilitate the generation of such databases in various fields, such as pharmaceuticals, genomics, and polymers (see the utilization of "gradient specimens" – URL: http://polymers.msel.nist.gov/combi/index.html).

Large datasets do not necessarily imply more complex analyses and processing needs. In fact, proper data display may often suffice for feature extraction:

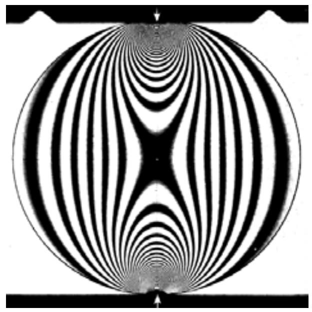
- gathering 10 sparse ground penetrating radar GPR signals and doing extensive physics-based inversion to infer the subsurface vs. gathering hundreds of signals and displaying them side-by-side to generate a typical GPR space-time image with virtually no data processing;
- complex signal processing of video images to guide vehicles for the blind vs. simple and robust audible clues from multiple acoustic sensors;
- identifying a tank from a vehicle in low resolution high-noise images through complex analysis-based vision software vs. cross-correlation with a databases of known images (C. Barnes – Georgia Tech Savannah).

These examples show that in some cases, more data lead to enhanced comprehension even when simpler analyses are used.

From "soils under study" $\xrightarrow{\text{to}}$ "Self-sensing geomaterials" (soils as innate sensors)

The soil (or rock mass) is not only the object under study, but it can be its own sensor as well. A soil particle is a deformable body, similar to a proofing ring in old triaxial systems (Figure 9). How can we recover force information in the case of soil grains in a soil mass? The propagation of elastic waves offers an alternative because the small strain stiffness is proportional to the normal contact force. This concept can be readily extended from Hertzian contacts between large grains to interparticle DLVO electrical interactions between small clay-size grains.

Other examples of self-sensing soil response include acoustic emission monitoring to assess the pre-consolidation pressure (Kaiser effect – Koerner et al. 1984), volumetric water content inferred from GPR to monitor volume contraction (Kayen et al. 2005), thermal imaging to identify thermo-elastic or thermo-plastic effects (Luong, 1985). Furthermore, grains can be engineered to amplify their sensing role (e.g., using selective coatings) and even react to changing conditions (e.g., saturating their internal porosity with selected fluids that become expelled upon crushing).



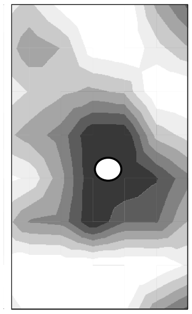


Figure 9. A soil grain ≡ Sensor. (a) Photoelastic disk subjected to a vertical force (Frotch, 1941). (b) Tomographic image of S-wave velocity around a pressured cavity "Stress tomography" (Lee et al. 2005)

From "commensurate data" $\xrightarrow{\text{to}}$ "complementary non-commensurate data"

There are various examples of data-fusion in geotechnology, including both "commensurate sensor networks" (e.g., the national earthquake seismograph network, geophone pairs or geophone arrays for seismic refraction and surface wave dispersion studies – Rix 2005) as well as "non-commensurate multi-mode sensor networks" (e.g., instrumentation in major excavations such as inclinometers, surface surveying points, pore pressure transducers, instrumented struts; multisensor laboratory cells such as an oedometer with probes for electrical conductivity, S- and P-wave propagation, temperature and thermal conductivity – Santamarina et al. 2001). The fusion of non-commensurate data can be implemented through a common underlying causal parameter. For example, the following boundary measurements and inverted fields depend on effective stress:

- boundary deformations invert to the field of volumetric strain $\varepsilon = C_c^{'} \log\left(\sigma_f^{'} / \sigma_o^{'}\right)$
- S-wave travel times invert to the field of shear wave velocity $V_s = \alpha\left[\left(\sigma_{||}^{'} + \sigma_{\perp}^{'}\right) / 2\text{kPa}\right]^{\beta}$
- electrical resistance between electrodes inverts to electrical conductivity $\sigma_{elec}^{soil} = n\sigma_{elec}^{fluid} = f\left(C_c, \sigma', \sigma_{elec}^{fluid}\right)$
- travel times for electromagnetic waves invert into the field of EM wave velocity $V_{EM} = \dfrac{c}{\sqrt{\kappa'}} = f(w) = f\left(C_c, \sigma'\right)$

Therefore, these multisensor data can be jointly considered or fused to infer the field of mean effective stress in the soil mass.

From "many simple tests" $\xrightarrow{\text{to}}$ "a few information-rich tests" (Laboratory and field testing)

Geotechnical laboratory test procedures and devices have evolved following clear guiding principles, such as (1) each test represents the conditions at point in the medium, therefore (2) the field under study (e.g., stress, strain, fluid pressure, chemical concentration) is homogeneous within the specimen. These guidelines have stimulated careful experimental design to attain uniform boundary conditions, tests that require minimal instrumentation, and data that can be readily interpreted (e.g., hydraulic conductivity measurements $k = qL/\left(\Delta h_t A\right)$). The "old paradigm" has served us well through simple and robust approaches.

However, every experiment is a physical reality that takes place in its full complexity. All we need is proper test design, extensive instrumentation and adequate analysis to extract all the needed information from a single test. The trend towards increased instrumentation has already started, and many soil cells are instrumented with transducers that permit monitoring the evolution of shear wave velocity and shear stiffness (e.g., bender elements), piezocrystals for P-wave velocity and bulk stiffness, thermocouples for heat generation and phase transformation, full boundary deformation field with lasers, acoustic emission for proximity to preconsolidation pressure or failure, various tomographic imaging strategies including X-rays absorption, shear wave velocity, electrical resistivity, and thermal IR imaging. Various groups are currently developing and implementing such tests (few examples include: K. Alshibly at LSU, B. Kutter at UC Davis, E. Romero at UPC-Barcelona; S. Foti at Politecnico di Torino; A. Rechenmacher at USC; M. Ismail at COFS-Perth; the author and co-workers at Georgia Tech).

Increasing the number of commensurate measurements does not add information if the internal fields are homogeneous, i.e., a specimen that deforms homogeneously provides identical data at all points. Therefore, the next step is to develop tests that purposely cause heterogeneous fields in order to increase the information content in measurements. Consider the photoelastic exercise documented in Figure 8. The prismatic specimen subjected to standard axial loading exhibits some minor stress concentrations at boundaries due to geometric imperfections in an otherwise homogeneous field. However, the stress and deformation fields become most informative about the material response when boundary loads are heterogeneous (Figure 8b).

Axial Loading (standard) *Axial + Flexural Loading*

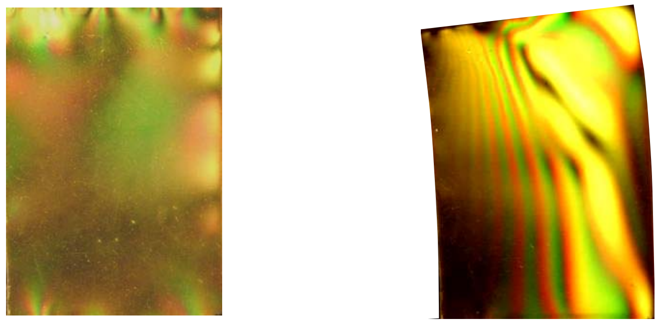


Figure 8. Increasing information content through non-homogeneous fields (Courtesy of A Bayoumi and TS Yun)

In the second case, the specimen stops representing a point. Instead, each point in the specimen captures the full complexity of the material, and boundary measurements are integrals of the internal field. Therefore, data interpretation changes from a simple algebraic inversion (say, $E = \Delta\sigma / \varepsilon$ in the first case) to a formal inversion. For example, the unique set of constitutive parameters would be extracted from non-standard load-deformation test by (1) considering all measured data at once, (2) within the framework of a pre-selected constitutive model, (3) using successive numerical simulations, (4) which are driven to minimize the error between measurements and the corresponding numerical predictions. Inversion complexities explored above gain full relevance in this context.

This discussion leads us to anticipate a paradigm shift in laboratory testing, changing from "*a large set of simple, low information content tests"* to "*a few, information-rich tests conducted on an intensively instrumented specimen"*. Table 5 compares laboratory testing under the old and new paradigms. There are already some publications that explore the new approach; analogous developments have also been taking place in the interpretation of in situ tests and evolving field data during construction (Arai et al. 1987; Hicher and Michali, 1996; Zentar et al 2001; Bayoumi 2005).

Table 5. Possible paradigm shift in laboratory measurements (applies to field studies as well)

	Old Paradigm	New Paradigm
Philosophy	many simple tests	a few, information-rich tests
Boundaries	simplest possible	complex boundary conditions
Field conditions	homogeneous field sought	heterogeneous field sought
Instrumentation	minimal instrumentation	extensive, multisensor
Measurements	very few	many, spatial and/or temporal
Interpretation - Inversion	simplest inversion	comprehensive inverse problem
Inferred information per test	very limited	as much as needed
Number of tests	many	one may be sufficient
Comprehensive characterization	required long time	potentially short time

From "Design&Construct" $\xrightarrow{\text{to}}$ ***"Predesign+Construct+Monitor+Adapt"***

R. Peck recognized that an alternative design-construction approach was instinctively followed in complex situations and distilled the methodology in a few steps known as the "observational method" (Peck 1969). Within the scope and terminology of this manuscript, the *observational method in the information age*, can be summarized as follows: (1) Assess conditions, establish working hypotheses, and produce a basic design, (2) preconceive possible deviations, alternative actions and design modifications, (3) select the parameters that must be measured during construction and design the sensor network/system to favor the invertibility of critical information, (4) once construction starts, gather the data, invert them to extract the information needed for decision making -see references in the previous section-, and (5) adapt the design as needed. The last step is a continuous feedback loop that is implemented throughout the construction phase.

Table 6 compares design and construction operations under the old and new paradigms. Developments in the information age effectively allow us to apply this methodology not only to complex situations but to virtually all construction projects. The inversion stage resembles constitutive model calibration discussed earlier, and it may incorporate spatial variability. The New Austrian Tunneling Method exemplifies this approach. Inversion-based efforts are documented in Asaoka and Matsuo (1980), Arai et al. (1984), Gioda and Sakurai (1987), Ledesma et al. (1996), Gens et al. (1996), Gioda and Locatelli (1999), Hashash et al. (2003), Finno and Calvello (2005). The feedback loop may be automated in some applications such as field compaction (noted by D. Fratta and E. Kavazanjian).

Table 6. Possible paradigm shift in design and construction: Observational method in the information age

	Old Paradigm	**New Paradigm**
Philosophy	safe design	adequate/optimal design
Sensor system	minimal	spatially distributed, multi-mode
During construction	sporadic measurements	continuous monitoring
Interpretation	minimal - limited use	continuous - extensively used
Inferred information	just measured data	comprehensive inversion
Total construction cost	higher than needed	important potential savings
Time demand	construction limited	construction limited
Safety	probably over designed	known adequate safety

Technological developments in the information age can take us even further. For example, foundations could remain instrumented after construction to monitor the soil-foundation interaction. Should the response change, polymeric substances or nutrients for cementing bacteria could be automatically injected to adapt the foundation to the new demands, just like tree roots. Utopia? Not really: smart, self-diagnosing and self-healing technology is already being implemented in other fields, including medicine.

The Human Side of The Information Age

As we walk into the information age, it is important to remind ourselves of important lessons we have learned about our ability to handle information. Few psychological and sociological comments follow.

The individual and information

Perception is not feasible in the absence of preconceptions, yet, pre-conceptions bias perception. We have several pervasive, innate fallacies in information processing and decision making (see Hogarth 1980). We tend to make decisions based on few cues (typically 4 or 5 – Miller's law establishes that we operate with 7±2 elements in short term memory). Once we have made a decision, additional data are selectively used to confirm our position and our false sense of certainty, rather than to challenge it. Therefore excess information is not only wasted but it may also be detrimental to decision making. Furthermore, we are biased by trends (Gambler's fallacy: "if red came out in the last 4 throws, the next one must be black").

At the same time, a trained mind can detect critical features with tremendous efficiency (trained psychologists can predict with 90% certainty whether a couple will divorce in the next 15 years by analyzing 15 minutes of husband and wife conversation! Gladwell 2005). We must remain alert that technology does not create a gap between us and the system under consideration: much insight is gained through direct interaction (i.e., interactive perception - Gibbson's cookie cutter experiments in the early 1960's). Therefore, we must continue investing in solid education, and facilitate the development of expertise through direct exposure to multiple case histories.

Sociological Aspects

Paradigm shifts can have profound sociological implications, even though their influence may advance almost imperceptibly: time measurement had a humble beginning in monasteries to help monks pray on time, but plays a crucial role in today's information technologies.

The exponential growth in communication capabilities has amplified the effects of the information revolution. Communications have removed the distance barrier among engineers and/or academicians at remote locations, and even facilitated the interaction with individuals in other disciplines.

Communications also facilitate outsourcing. So far, very limited amount of geotechnical work goes across states in the US or across national boundaries in the European Community. Still, one should expect that many aspects of outsourcing will continue developing in years to come, often to the advantage of US firms as long as they maintain a technological edge (see Friedman 2005 for a lucid and persuasive discussion of these issues).

The information age has the potential to benefit society as a whole. However, there are concerns about the widening digital gap between the "information rich" and the "information poor", which in turn contributes to widening the economic gap. The effects manifest across generations, social classes and countries. The World Federation of Engineering (2003) has challenged engineers to adapt information technology for the benefit of people, in particular the poor, in the belief that innovation and research will find solutions to problems generated by the new information age. Furthermore, WFE has proposed a vision of the Information Society that is open and inclusive, that promotes the diffusion of knowledge and facilitates the sharing of information, that values the development of human beings, and respects cultural and linguistic diversity.

Educational Needs for Geotechnology in the Information Age

The information age will continue diffusing into all aspects of geotechnology research and practice, enhancing both our ability to further understanding the fundamental behavior of geomaterials and to address societal needs. Based on the previous discussion, our study programs need to provide students with working knowledge on: commercially available sensors and sensor networks (including communications), databases, and discrete mathematics to address signal processing and inverse problem solving, and on the application of numerical methods. Above all, engineering students must recognize that the new technology enables them to approach problem solving with renewed ingenuity.

The information age affects the way we do things, but it does not change Nature's way. Therefore, the new educational goals may replace current "how-to-do" training, but we must not downgrade students education in the fundamental understanding of geomaterials and related physical, mechanical, chemical and biological principles.

Closing thoughts: a New Geotechnical Era

We are witnesses to unprecedented concurrent growth in various fields that together sustain the ongoing information revolution. In the meantime, the geotechnical field has reached an in-depth understanding of geomaterials and subsurface processes, and has developed advanced models for numerical simulations. In so doing, our field is prepared to gain maximum benefit from information technology.

Embracing information technology will trigger important changes in the way we teach, learn, investigate and approach problem solving. But technology must not detach us from the physical reality: new solutions cannot circumvent the fundamental physical, chemical and biological laws that govern the behavior of geomaterials.

Today, our ability to measure has surpassed our material models in many ways. Still, there is still a role for good, reliable sensors, simple data gathering procedures, and standard back-analyses. Above all, there is a critical role for great engineering. In fact, it is in this time of changes when we need our best engineering skills and ingenuity to explore new problem solving strategies.

In the midst of rapid changes, let's remember the principles that remain unaffected in data gathering and information extraction:

- sensing implies energy interaction, hence, the measurement always affects the measurand;
- data do not imply information, and remain meaningless without understanding;
- inversion magnifies data and model errors.

Furthermore, let's remain keenly aware of potential differences between "what you want to measure, what you think you measure, and what you measure" (source unknown).

Developments in the information age allow us to reinvent geotechnology one more time. Take a few minutes. Imagine what the field of geotechnology could become if we had unlimited access to spatial and temporal data of all kinds, readily searchable comprehensive databases, powerful user friendly analysis and simulation software… Let's imagine --and act on our imagination-- now.

Disclaimer

Space, time and knowledge limitations have not allowed me dwell on other important developments in data display and GIS, global positioning systems, remote sensing and geophysics, image processing technology (many recent geotechnical publications), powerful laboratory equipment (including tomographers of all kinds), and the ability to conduct ever more sophisticated numerical experiments. Contributions to this conference illuminate these and many other topics missing in this document.

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