Inferring Pile Shape from Pulse-Echo Test Records by Evolutionary Algorithm

Erez I. AMIR

President, Piletest.com Ltd. Erezam@piletest.com

Joram M. AMIR

Chairman, Piletest.com Ltd. JMAmir@Piletest.com

Keywords: Low Strain impact integrity Testing, Signal Matching, Inverse problems, Evolutionary Algorithms, Genetic Algorithms.

ABSTRACT:

The pulse echo method (PEM) is without doubt the most widespread test for pile integrity evaluation and is applied to millions of piles annually. Inferring a pile's shape from the obtained results is a classical inverse problem which is usually skipped and done qualitatively by an experienced engineer. Once digital testing systems became available to engineers, attempts were made to solve this problem by dedicated algorithms. Several of these methods work well on textbook examples, but not so well when faced with difficult cases such as slender piles embedded in soil with high friction or piles with an irregular profile. High amount of signal processing is required for analyzing those signals and solving the problem becomes harder.

Theoretically, inverse problems have an infinite number of solutions. In order to find the most probable one, we have to apply all available information, and in addition make some reasonable assumptions. The algorithm should be efficient and the solution must be consistent and plausible.

In this paper we present a method based on an evolutionary algorithm (random mutations and survival of the fittest) which works efficiently on such cases and produces consistent and reasonable results.

The necessary input includes the wave speed in the pile, the reported pile length and the soil friction profile. The assumptions include the validity of the one-dimensional wave equation and the requirement that the pile profile must be reasonably smooth. The hammer blow record in the reflectogram serves as an initial condition.

Although the algorithm is based on random mutations, experience has shown that consecutive runs converge to essentially similar pile shapes.

1 INTRODUCTION

In the sonic (alias low strain or pulse-echo) method for pile integrity testing (ASTM 2007) the top of the pile is tapped with a lightweight plastic hammer and the reflected waves are recorded by a sensor placed on the top of the pile. This method was introduced in the early 1970's (Steinbach and Vey 1975) and soon after analog equipment and then digital systems became commercially available. Today the method is considered the primary means for pile quality assurance, being annually applied to millions of piles worldwide. The availability of digital output lead to attempts of extending the usefulness of the method by plotting the pile shape from the time history of pile head velocity (Kido et al. 1988). These attempts yielded encouraging results as long as the data was synthetic and soil friction was disregarded.

The so-called Impedance Log approach, which assumes full soil data for each pile tested, claims the ability to plot the shape of the tested pile embedded in soil (Hertlein and Davis 2006).

Although it has been proved that it is theoretically impossible to plot a unique pile profile from the sonic test results, such a plot can still serve as an important visualization and interpretation aid.

2 BACKGROUND

2.1 *Pulse-echo method*

All modern testing systems record the time history of particle velocity at the pile head, starting with the hammer blow. The output of the transducer is fed into suitable computerized equipment which processes and displays the data. The resulting signal, or reflectogram, depends on the length and shape of the pile as well as by the surrounding soil.

below (Figure 1, Figure 2 Figure 3) are some examples of such reflectograms:

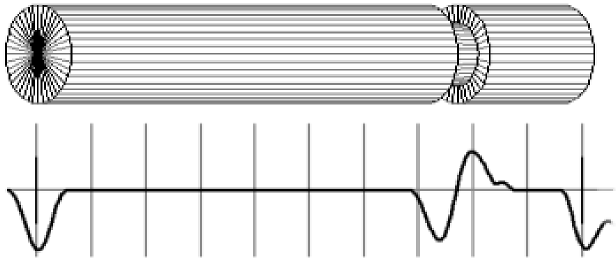

Figure 1: A pile with a reduced cross-section and the resulting reflectogram (Synthetic)

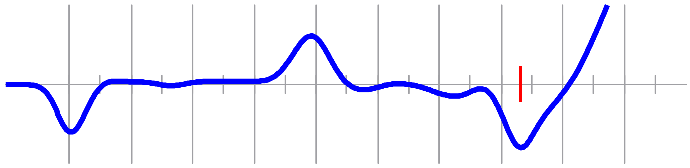

Figure 2: A reflectogram of a real pile with an apparently increased cross-section

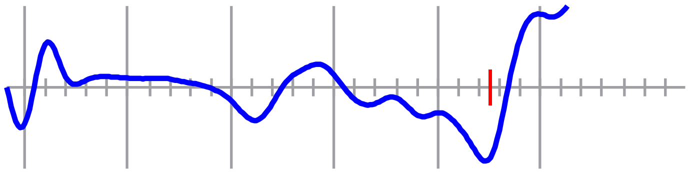

Figure 3: A reflectogram of a real pile with an apparently reduced cross-section

2.2 *Inferring the pile shape from Pulse-echo results*

Inferring the pile shape from the reflectogram is an inverse problem that has no unique solution. Even in the simplest textbook cases, with no soil friction and no signal processing an infinite number of pile profiles can provide almost identical reflectograms (Schellingerhout and. Muller, 1996)

When testing slender piles in hard soils, the reflectogram traces may become noisy and faint, hence requiring extensive signal processing for the results to become useful. Such processing includes filtering, sharpening, exponential amplification and more. Figure 4 shows such a result where high amplification (X200) is needed to examine the toe reflection.

Under such real-life conditions, not only is there no unique solution, but the problem becomes harder to solve using the standard methods.

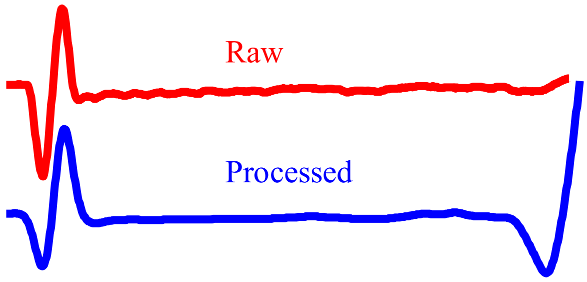

Figure 4: Same reflectogram, before and after processing

Although admittedly not unique, the proposed method provides repeatable results which provide a meaningful visual aid for interpretation purposes.

2.3 *Evolutionary Algorithms*

An Evolutionary Algorithm (EA) is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems. (Sivanandam & Deepa, 2006). The main elements of the EA are:

- the population is represented by a set of candidate models $M_1 \ldots M_n$
- Mutations are represented by random changes to the models $M_x \rightarrow \acute{M}_x$
- “Survival of the fittest” principle is represented by a target function *f(M)*

At each cycle (“generation”) randomly modified model copies $\acute{M}_1 \ldots \acute{M}_n$ (Mutants) are generated and the target function *f* is than used to select the best ones. Most modified models cause *f(M)* to decrease and these are deleted and forgotten. Some changes, however, increase *f(M)* and become a part of the surviving model set by replacing their predecessors.

Although the mutations are random, the algorithm is stable and monotonic (always improving). EA may incorporate a-priori knowledge to limit and direct the randomness of the mutations.

EA has several advantages over other search and optimization methods such as gradient ascent and random search: It is quick, does not tend to get trapped in local maxima, is simple to implement and allows seamless integration with a-priori knowledge.

3 THE ALGORITHM

When applied to inferring pile shape, the proposed evolutionary algorithm takes the following form:

1. **Manual phase:**
   1.1. The operator manually edits the pulse-echo data and brings the measured trace t_m to a normalized form:

amplification and filter values are selected to show the main features (Figure 4) of the measured trace. The pile's assumed length L is also indicated by the operator.
   - 1.2. An initial "seed" model M_0: a cylindrical pile with length=L is generated.
   - 1.3. A simulation is run on the M_0 and the operator is shown a superposition of both measured and calculated traces (t_m and t_c)
   - 1.4. The operator may manually modify M_0 to get a rough match t_m and t_c
2. **Evolution phase:**
   - 2.1. M_0 is copied N times (typically N=10) to create M_1, M_1, …M_N
   - 2.2. **Mutation**: Each model M_i is copied. One copy is kept unchanged and one copy is being changed randomly to create $\acute{M}_i$
   - 2.3. **Fitness**: A forward-model simulation is run on each of the 2N mutants. the resulting calculated trace t_c is compared to the measured trace t_m using the target function *f(M)*.
   - 2.4. **Selection:** The N best matching models are kept and renamed M_1, M_1, …M_N the others are discarded and forgotten.
   - 2.5. The best matching trace is dynamically displayed to the operator.
   - 2.6. Mutation phases 2.2-2.5 are repeated indefinitely until stopped by the operator. The operator may at any stage return to the manual phase, make some changes and than re-launch the algorithm.

3.1 *Algorithm details*

3.1.1 Model

The pile shape is represented by a vector of k <diameter, length> points ($p_1=\langle d_1,l_1\rangle$, …, $p_n=\langle d_n,l_k\rangle$). For example: a cylindrical pile of diameter D and length L only requires 2 such points ($\langle D,0\rangle$,$\langle D,L\rangle$). This compact model holds the following advantages:

1. Significant changes to the profile can be generated by a small change to the model.
2. Slicing of the model (converting it to a set of cylinders, required for the wave equation calculations) can be done at any resolution, permitting a tradeoff between accuracy and speed. In the initial evolution generations, rough and quick models are constructed and refined later on.

Soil friction profile is represented by a similar vector.

3.1.2 Mutations

One or more of the following changes are applied to the copies model:

1. A point p_x is inserted
   $(p_1,\ldots p_k) \rightarrow (p_1,\ldots p_x,\ldots p_{k+1})$
2. A point is deleted
   $(p_1,\ldots p_x,\ldots p_{k+1}) \rightarrow (p_1,\ldots p_k)$
3. A point is moved (replaced)
   $(p_1,\ldots p_x,\ldots p_k) \rightarrow (p_1,\ldots p'_x,\ldots p_k)$
4. All the points D values are multiplied by a fixed value x close to 1.0
   for each i=1..k, $\langle d_i, l_i\rangle \rightarrow \langle x\cdot d_i, l_i\rangle$
5. The model is being merged with another model to produce an "average" model

The mutations can be applied to both the pile profile and the soil friction distribution. We have reached the best results by limiting the soil friction profile mutations to #4 above. This merits additional research.

3.1.3 Target (Fitness) function

Initial target function was solely based on curve fitting. Later on we have found out that this caused the algorithm to arrive at very complex models which were just marginally better than the simple ones. Adding "simplicity" as 10% of the target function makes the algorithm break nearly-identical ties between two candidate models in favor of the simpler one.

The curve fitting score (90%) is based on a simulation performed on the model. Identical signal processing parameters are than applied to the calculated reflectogram, which is in turn compared to the measured reflectogram.

The simplicity score (10%) is based on the model profile length: The total linear dimension of the model ($\langle d_1,l_1\rangle,\langle d_2,l_2\rangle\ldots\langle d_k,l_k\rangle$) is compared to the length of the pile L. Longer lines (which correspond to a more complex model) are assigned a lower fitness value.

3.1.4 Simulation

The simulation takes the following parameters:

- Pile profile
- Soil friction profile
- Impact shape - taken from measured trace

The output of the simulation is the pile head particle velocity vs. time (Reflectogram). Signal processing parameters are identical to those applied on the measured data are used.

During the execution of the algorithm, the simulation is run on each mutant model at each generation, for many thousands of times. Special care was taken to optimize the time performance of the simulation.

3.1.5 Optimizations

- In order to avoid getting trapped in local maxima, the algorithm mutates the worstranked models wildly, while the best ranking models only get fine tuning.

- At the initial generations, the model is being sliced to a relatively small number of cylinders (See 3.1.1) which speeds up the simulation significantly. As the evolution progresses and converges slicing is dynamically refined.
- The operator may manually restrict the algorithm to perform model changes only in a desired depth range. This is useful if the experienced operator does not expect any significant changes to the profile outside this range.

4 PERFORMANCE ANLISYS

4.1 *Repeatability*

The algorithm usually reaches very close results at each run (Figure 5). Since we know (Schellingerhout and. Muller, 1996) that there is infinite number of solutions (profiles) that generate nearly identical reflectograms, this result might appear surprising. It is assumed (although this merits further research) that in some cases, the infinite set of possible profiles still shows common characteristics which can be seen a unique solution, for all practical purposes.

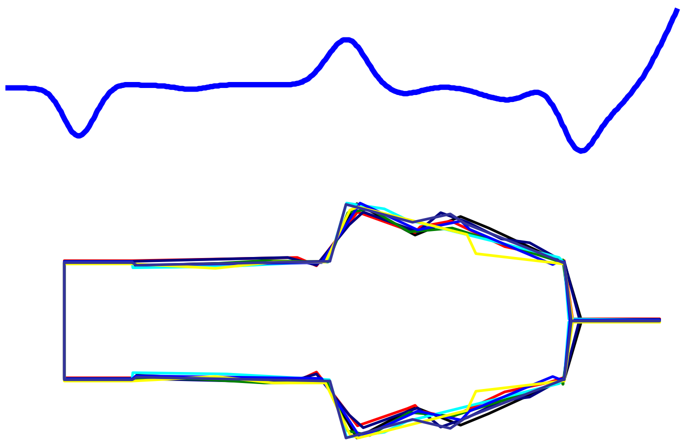

Figure 5: Pile profile- results of 10 runs, superimposed.

4.2 *Convergence*

After each generation, the best model (the model with the highest target function value is presented to the operator along with a "match quality" index (which is based on the target function value). The operator may stop the evolution progress at any time and print/save the results, modify the model manually, re-start the evolution, etc.

5 FURTHER RESEARCH

The following items merit further work to enhance the effectiveness of the method:
On suitable sites, calculate the average reflectogram for piles of similar length, and using it by EA to calculate the representative friction distribution for the site.

After the method is applied in practice by multiple users, analyze the results to define the conditions where the method fails to converge or produces anomalous results.

6 CONCLUSIONS

In this paper we have introduced the method of evolutionary algorithms to infer the pile shape from sonic test results (reflectograms). We have shown that the method is viable, consistent and serves as a helpful analysis and visualization tool.

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