Neural Inverse Space Mapping EM-Optimization

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Neural Inverse Space Mapping EM-Optimization (NISM)

outline

ANN approaches for microwave design

NISM optimization

statistical parameter extraction

inverse neuromapping

the NISM step vs. the quasi-Newton step

examples

conclusions
Conventional ANN-Based Optimization of Microwave Circuits

step 1

ANN

fine model

\[ \omega \]

\[ x_f \]

\[ R_f \approx R_f \]

step 2

ANN

\[ \omega \]

\[ x_f \]

\[ R^* \]

many fine model simulations are usually needed
solutions predicted outside the training region are unreliable
ANN-Based Microwave Optimization Exploiting Available Knowledge

EM-ANN approach
(Gupta et al., 1999)

neural space mapping approach
(Bandler et al., 2000)

NSM optimization requires $2n+1$
upfront fine simulations
Objectives

develop an aggressive ANN-based space mapping optimization

avoid multipoint parameter extraction and frequency mappings
Neural Inverse Space Mapping Optimization

PARAMETER EXTRACTION:
Find $x_c^{(i)}$ such that
\[ R_{cs}(x_c^{(i)}) \approx R_{fs}(x_f^{(i)}) \]

INVERSE NEUROMAPPING:
Find the simplest neural network $N$ such that
\[ x_f^{(i)} \approx N(x_c^{(i)}) \]

$\quad l = 1, \ldots, i$

COARSE OPTIMIZATION: find the optimal coarse model solution $x_c^*$ that generates the desired response

$\quad x_f^{(i)} = x_c^*$

Calculate the fine responses $R_{fs}(x_f^{(i)})$
Statistical Parameter Extraction

\( x_c^{(i)} = \arg \min_{x_c} U_{PE}(x_c) \)

\( U_{PE}(x_c) = \| e(x_c) \|_2^2 \)

\( e(x_c) = R_{fs}(x_f^{(i)}) - R_{cs}(x_c) \)

\( \Delta_{\text{max}} = \frac{\delta_{PE}}{\| \nabla U_{PE}(x_c^*) \|_\infty} \)

\( \Delta x_k = \Delta_{\text{max}} (2 \text{rand}_k - 1) \quad k = 1 \ldots n \)

```
begin
  solve (1) using \( x_c^* \) as starting point
  while \( \| e(x_c^{(i)}) \|_\infty > \varepsilon_{PE} \)
    calculate \( \Delta x \) using (2) and (3)
    solve (1) using \( x_c^* + \Delta x \) as starting point
end
```
Inverse Neuromapping

\begin{equation}
\begin{align*}
w^* &= \arg \min_w U_N(w) \\
U_N(w) &= \| [ \cdots e_i^T \cdots]^T \|_2^2 \\
e_i &= x_f^{(l)} - N(x_c^{(l)}, w) \\
l &= 1, \ldots, i
\end{align*}
\end{equation}

ANN (2LP or 3LP)

\begin{align*}
x_c &\rightarrow N \rightarrow x_f \\
w &\downarrow
\end{align*}

\begin{algorithm}
\begin{enumerate}
\item solve (4) using a 2LP
\item $h = n$
\item while $U_N(w^*) > \varepsilon_L$
\item solve (4) using a 3LP
\item $h = h + 1$
\end{enumerate}
\end{algorithm}
Nature of the NISM Step

\[ x_f^{(i+1)} = N(x_c^*) \]

evaluates the current ANN at the optimal coarse solution

is equivalent to a quasi-Newton step

departs from a quasi-Newton step as the nonlinearity needed in the inverse mapping increases

does not use classical updating formulas to approximate the Jacobian inverse
Termination Condition for NISM Optimization

$$\| x_f^{(i+1)} - x_f^{(i)} \|_2 \leq \varepsilon_{end} (\varepsilon_{end} + \| x_f^{(i)} \|_2) \quad \lor \quad i = 3n$$
we take \( L_0 = 50 \text{ mil} \), \( H = 20 \text{ mil} \), \( W = 7 \text{ mil} \), \( \varepsilon_r = 23.425 \), loss tangent \( = 3 \times 10^{-5} \); the metalization is considered lossless

the design parameters are

\[
x_f = [L_1 \ L_2 \ L_3 \ S_1 \ S_2 \ S_3]^T
\]

specifications

\[
|S_{21}| \geq 0.95 \text{ for } 4.008 \text{ GHz} \leq \omega \leq 4.058 \text{ GHz}
\]

\[
|S_{21}| \leq 0.05 \text{ for } \omega \leq 3.967 \text{ GHz} \text{ and } \omega \geq 4.099 \text{ GHz}
\]
HTS Microstrip Filter: Fine and Coarse Models

fine model:
Sonnet’s *em™* with high resolution grid

coarse model:
OSA90/hope™ built-in models of open circuits, microstrip lines and coupled microstrip lines
NISM Optimization of the HTS Filter

responses using $em^\text{TM}$ (○) and OSA90/hope$^\text{TM}$ (−)

at the starting point
NISM Optimization of the HTS Filter (continued)

responses using OSA90/hope™ (−) at $x_c^*$ and $em$™ (○) at the NISM solution

(after 3 NISM iterations)
NISM vs. NSM Optimization

HTS filter optimal responses in the passband

after NISM (3 fine simulations)  

after NSM (14 fine simulations)  

(Bandler et al., 2000)
NISM vs. Trust Region Aggressive Space Mapping (TRASM) Exploiting Surrogates

fine model minimax objective function

after NISM (3 fine simulations)

after TRASM Exploiting Surrogates
(8 fine simulations) \( (Bakr \ et \ al., \ 2000) \)
Conclusions

we propose Neural Inverse Space Mapping (NISM) optimization

up-front EM simulations, multipoint parameter extraction or frequency mapping are not required

a statistical procedure overcomes poor local minima during parameter extraction

an ANN approximates the inverse of the mapping

the next iterate is obtained from evaluating the ANN at the optimal coarse solution

this is a quasi-Newton step

NISM optimization exhibits superior performance to NSM optimization and Trust Region Aggressive Space Mapping Exploiting Surrogates