## Note

# Numerical Computations on One-Dimensional Inverse Scattering Problems* 


#### Abstract

In this note we present an approximate method to detemine the index of refraction of a dielectric obstacle. For simplicity we treat one-dimensional models of electromagnetic scattering. The governing equations yield a second-order boundary value problem, in which the index of refraction appears as a functional parameter. The availability of reflection coefficients yields an additional initial condition. We approximate the index of refraction by a $k$ thorder spline which can be written as a linear combination of $B$-splines. For $N / 2$ distinct reflection coefficients, the resulting $N / 2$ initial value problems yield a system of $N$ nonlinear equations in $N$ unknowns which are the coefficients of the $B$-splines.


## 1. Introduction

In this note we treat a class of inverse scattering problems in one dimension. We seek a function $n(x)$, which we refer to as the index of refraction, such that the solution of the boundary value problem

$$
\begin{align*}
u^{\prime \prime}(x)+n^{2}(x) \omega^{2} u(x) & =0, \quad x \in(0,1) \\
\left(u^{\prime}+i n_{0} \omega u\right)(0) & =2 i n_{0} \omega  \tag{B}\\
\left(u^{\prime}-i n_{0} \omega u\right)(1) & =0
\end{align*}
$$

satisfies $u(0)=1+R(\omega)$ and $u^{\prime}(0)=i n_{0} \omega(1-R(\omega))$, where $R(\omega)$ is called the reflection coefficient. In practice $R(\omega)$ can be measured for any desired value of $\omega$. The problem can be thought of as arising from the refraction of an incident wave of the form $e^{i n_{0} \omega x}$ by a dielectric obstacle whose index of refraction is unknown. See [1] for a complete physical derivation of the boundary value problem (B).

This problem has also been studied by Hagin [2] and Gray and Hagin [3]. A similar problem has been studied by Schaubert and Mittra [4] and Tsien and Chen [5].

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## 2. Solution Procedure

Our solution procedure consists of approximating $n(x)$ with a $k$ th-order spline $\bar{n}(x)$. This choice of approximation is motivated by the need to solve the initial value problem

$$
\begin{align*}
u^{\prime \prime}+\omega^{2} \bar{n}^{2} u & =0, \quad x \in(0,1) \\
u(0) & =1+R(\omega)  \tag{P}\\
u^{\prime}(0) & =i n_{0} \omega(1-R(\omega))
\end{align*}
$$

quickly and accurately.
We begin with a brief description of the spline spaces $S_{k}(\mathbf{x})$. Let $\mathbf{x}=\left\{x_{i}\right\}_{i=1}^{N+1}$ be a partition of $[0,1]$, and let $S_{k}(x)$ denote the space of $k$ th-order splines with knots at each $x_{i}$. Thus, $s \in S_{k}(\mathbf{x})$ implies that in each interval $\left[x_{i}, x_{i+1}\right], s$ is a polynomial of degree at most $k-1$ and $s \in C^{(k-2)}[0,1]$. Let $\left\{B_{i, k}\right\}_{i=1}^{N+k-1}$ denote the $B$-spline basis for $S_{k}(\mathbf{x})$. The general properties of $B$-splines are well known and can be found in [6], for example. A property that we find convenient for our numerical scheme is that $B_{i, k}(x)=0$ if $x \notin\left[x_{i-k \pm 1}, x_{i+1}\right]$. As a consequence, if $f(x)=\sum_{i=1}^{\bar{N}} \alpha_{i} B_{i, k}(x)$ and if $x \in\left[x_{m}, x_{m+1}\right]$, where $\bar{N}=N+k-1$, then $f(x)$ is simply given by

$$
\begin{equation*}
f(x)=\sum_{i=m}^{m+k-1} \alpha_{i} B_{i, k}(x) . \tag{2.1}
\end{equation*}
$$

The approximation of $n$ proceeds as follows: For given $N$ and $k$ we seek an approximation $\bar{n}(x)=\sum_{i=1}^{\bar{N}} \lambda_{i} B_{i, k}(x)$ such that, given the distinct pairs $\left(\omega_{j}, R\left(\omega_{j}\right)\right)$, $j=1, \ldots, l$, where $l=|\bar{N} / 2|$, the solutions of the $l$ initial value problems ( P ) satisfy $\left(u^{\prime}-i \omega_{j} u\right)(1)=0$. This is equivalent to solving

$$
\begin{equation*}
F(\lambda)=0 \tag{2.2}
\end{equation*}
$$

where $\lambda=\left(\lambda_{1}, \ldots, \lambda_{N}\right)^{T}$ and $\mathbf{F}(\lambda)=\left(f_{1}(\lambda), \ldots, f_{N}(\lambda)\right)^{T}$ with $f_{2 j}=\operatorname{Real}\left(\left(u^{\prime}-i \omega_{j} u\right)(1)\right)$ and $f_{2 j-1}=\operatorname{Imag}\left(\left(u^{\prime}-i \omega_{j} u\right)(1)\right), j=1,2, \ldots, l$.

In order to solve (2.2) one must solve ( P ) many times. In general this requires the numerical solution of these problems which leads to a large cost in computer time. Our choice of approximation reduces this time to a great extent. For example, when $k=1, \bar{n}$ is piecewise constant, thus one can obtain the solution of ( P ) in closed form, and when $k \geqslant 2$ one can easily obtain symbolic Taylor series expansions of $u$. The Taylor expansions are computed as follows: For $x \in\left[x_{m}, x_{m+1}\right], \bar{n}(x)$ is a polynomial of degree at most $k-1$ and is given by $\bar{n}(x)=\sum_{i=m}^{m+k-1} \lambda_{i} B_{i, k}(x)$. This follows from (2.1). Let $S_{m}(x)$ and $H_{m}(x)$ denote two linearly independent Taylor series solutions, expanded about $x_{m}$, of $(\mathrm{P})_{1}$ that satisfy $S_{m}\left(x_{m}\right)=H_{m}^{\prime}\left(x_{m}\right)=1$ and $S_{m}^{\prime}\left(x_{m}\right)=$ $H_{m}\left(x_{m}\right)=0$. Let $a_{1}=1+R(\omega)$ and $b_{1}=\operatorname{in}_{0} \omega(1-R(\omega))$, then for $x \in\left[x_{m}, x_{m+1}\right]$ the
solution of (P) is given by $u(x)=a_{m} S_{m}(x)+b_{m} H_{m}(x)$, where $a_{m}=a_{m-1} S_{m-1}\left(x_{m}\right)+$ $b_{m-1} H_{m-1}\left(x_{m}\right)$ and $b_{m}=a_{m-1} S_{m-1}^{\prime}\left(x_{m}\right)+b_{m-1} H_{m-1}^{\prime}\left(x_{m}\right)$ for $m=2,3, \ldots, N+k$. For comparative purposes the solution of (2.2) was obtained by solving ( P ) with a fourthorder, variable step size Runge and Kutta integrator. This resulted in a fivefold increase in computer time.

It is known [6] that if $f \in C^{(j)}[0,1]$ for $j=0,1, \ldots, k-1$, then $\inf _{s \in S_{k}(\mathbf{x})}\|f-s\|_{\infty} \leqslant C_{k, j} h^{j} w\left(f^{(j)} ; h\right)$, where $h=\max _{1 \leqslant i \leqslant N}\left(x_{i+1}-x_{i}\right), \quad C_{k, j}$ is a constant which depends only on $k$ and $j$ and

$$
w\left(f^{(j)} ; h\right):=\sup \left\{\left|f^{(j)}(x)-f^{(j)}(y)\right|: x, y \in[0,1],|x-y| \leqslant h\right\}
$$

is the modulus of continuity of $f^{(j)}$ at $h$. It is also known that the above estimate cannot be improved. Thus, if $n \in C^{(k)}[0,1]$, then $w\left(n^{(k-1)} ; h\right) \leqslant h\left\|n^{(k)}\right\|_{\infty}$ and the best that we can hope for is $\|n-\bar{n}\|_{\infty}=O\left(h^{k}\right)$. As will be seen, in several numerical examples tested the optimal convergence rate was attained.

## 3. Numerical Results

In this section we present some numerical examples for $k=1,2$ and 3 with knot sequence $\{(i-1) / N\}_{i-1}^{N+1}$. In all examples the Levenberg-Marquardt algorithm [7] was used to solve (2.2). The $R\left(\omega_{j}\right)$ 's were computed by inputting the exact solution $n(x)$ into (B). All computations were done on the Cyber- 173.

To solve a large nonlinear system of equations it is usually necessary to have a good initial approximation to the solution. For fixed $N$ and $k$ our solution was built up according to the following algorithm:
(i) Select a sequence of integers $\mathbf{m}=\left\{m_{i}\right\}_{i=1}^{M}$ with $m_{1} \geqslant k, m_{M}=\bar{N}$ and $m_{i}<m_{i+1}$.
(ii) Compute $\bar{n}_{m_{1}}$ by solving (2.2) with an initial guess $\lambda_{1}=\cdots=\lambda_{m_{1}}=1$.
(iii) For $j=1, \ldots, M-1$ compute $\bar{n}_{m_{j+1}}$ by solving (2.2) with the initial guess chosen so that $\bar{n}_{m_{j+1}}$ interpolates $\bar{n}_{m_{j}}$ at the $m_{j+1}$ distinct points $\left\{y_{i}\right\}_{i=1}^{m_{j}+1}$. This gives a linear system for the initial $\lambda_{i}$ 's that is invertible if and only if

$$
x_{i}<y_{i}<x_{i \mid k}, \quad i=1, \ldots, m_{j \backslash 1}[6] .
$$

We found that adequate results were obtained by setting $\mathbf{m}=\left\{2^{i}\right\}_{i=1}^{M}$ for $k=1$, and $\mathbf{m}=\{4 i\}_{i=1}^{M}$ for $k=2$ and 3.

The maximum attainable $\bar{N}$ is limited by considerations of computer time and accuracy. In the examples tested we found that satisfactory results were obtained if $\bar{N}=32$ for $k=1$ and $\bar{N}=8$ or 12 for $k=2$ and 3 .

Example 1 (Figs. 1,5, 9).

$$
n(x)=1+x^{2} .
$$

TABLE I

|  | $k$ | 1 | 2 |
| :--- | :---: | :---: | :---: |
| 3 |  |  |  |
| $\bar{N}$ | 32 | 12 | 12 |
| $\\|n-\bar{n}\\|_{\infty}$ | 0.033 | 0.0033 | $1 \times 10^{-7}$ |
| $\\|n-\bar{n}\\|_{2}$ | 0.014 | 0.0011 | 0 |
| Computational time (CPU sec) | 74 | 22 | 24 |
| Estimated convergence rate | 1.0 | 2.1 | - |

Example 2 (Figs. 2, 6, 10).

$$
n(x)= \begin{cases}1, & x \in\left[0, \frac{1}{4}\right) \cup\left(\frac{3}{4}, 1\right] \\ 1+\sin ^{2} 2 \pi\left(x-\frac{1}{4}\right), & x \in\left[\frac{1}{4}, \frac{3}{4}\right] .\end{cases}
$$

TABLE II

| $k$ | 1 | 2 | 3 |
| :--- | :---: | :---: | :---: |
| $\bar{N}$ | 32 | 12 | 12 |
| $\\|n-\bar{n}\\|_{\infty}$ | 0.12 | 0.071 | 0.065 |
| $\\|n-\bar{n}\\|_{i}$ | 0.032 | 0.18 | $5.5 \times 10^{-4}$ |
| Computational time (CPU sec) | 120 | 41 | 33 |
| Estimated convergence rate | 1.1 | 0.96 | - |

Example 3 (Figs. 3, 7, 11).

$$
n(x)= \begin{cases}1, & x \in\left[0, \frac{1}{2}\right) \\ 2, & x \in\left[\frac{1}{2}, 1\right] .\end{cases}
$$

TABLE III

| $k$ | 1 | 2 | 3 |
| :--- | :---: | :---: | :---: |
| $\bar{N}$ | 16 | 8 | 8 |
| $\\|n-\bar{n}\\|_{\infty}$ | 0.49 | 0.48 | 0.46 |
| $\\|n-\bar{n}\\|_{2}$ | 0.17 | 0.10 | 0.013 |
| Computational time (CPU sec) | 27 | 12 | 7.0 |
| Estimated convergence rate | - | - | - |

Example 4 (Figs. 4, 8, 12).

$$
n(x)= \begin{cases}1, & x \in\left[0, \frac{1}{4}\right) \\ \frac{1}{2}+2 x, & x \in\left[\frac{1}{4}, \frac{3}{4}\right] \\ 2, & x \in\left(\frac{3}{4}, 1\right]\end{cases}
$$

TABLE IV

| $k$ | 1 | 2 | 3 |
| :--- | :---: | :---: | :---: |
| $\bar{N}$ | 32 | 12 | 12 |
| $\\|n-\bar{n}\\|_{\infty}$ | 0.038 | 0.024 | 0.023 |
| $\\|n-\bar{n}\\|_{2}$ | 0.015 | 0.0074 | $4.4 \times 10^{-5}$ |
| Computational time (CPU sec) | 168 | 46 | 24 |
| Estimated convergence rate | 1.1 | 1.1 | - |

In practice the measurement of the reflection coefficients is subject to experimental error. To simulate this situation we introduced Gaussian-type noise in the values of $R(\omega)$ in the form $R(\omega)+\varepsilon a /|R(\omega)|$, where $a$ is Gaussian random number with mean $=0$ and standard derivation $=1$ and $\varepsilon$ is an "amplitude" factor to be adjusted. As the following tables indicate stable results were obtained when $\varepsilon$ was less than $10^{-3}$.

## Example 5.

$$
n(x)=1+x^{2}, \quad k=2, \quad \bar{N}=8
$$

TABLE V

| Comp. time | $\varepsilon /\|R(\omega)\|$ | $\\|n-\bar{n}\\|_{2}$ | $\\|n-\bar{n}\\|_{\infty}$ |
| :---: | :---: | :---: | :---: |
| 6.0 | 0 | 0.0019 | 0.0054 |
| 7.9 | $10^{-5}$ | 0.0093 | 0.026 |
| 12 | $10^{-4}$ | 0.070 | 0.19 |
| 25 | $10^{-3}$ | 0.34 | 1.0 |

Example 6.

$$
n(x)= \begin{cases}1, & x \in\left[0, \frac{1}{4}\right) \\ \frac{1}{2}+2 x, & x \in\left[\frac{1}{4}, \frac{3}{4}\right], \\ 2, & x \in\left[\frac{3}{4}, 1\right] .\end{cases}
$$

TABLE VI

| Comp. time | $\varepsilon /\|R(\omega)\|$ | $\\|n-\bar{n}\\|_{2}$ | $\\|n-\bar{n}\\|_{\infty}$ |
| :---: | :---: | :---: | :---: |
| 14 | 0 | 0.22 | 0.061 |
| 19 | $10^{-5}$ | 0.012 | 0.031 |
| 22 | $10^{-4}$ | 0.081 | 0.20 |
| 34 | $10^{-3}$ | 0.38 | 1.1 |

## 4. Discussion

In all noiseless examples with $k=1$ and 2, except for Example 3, the optimal convergence rate was attained.


Figs. 1-4. $k=1$.


Figs. $5-8 . \quad k=2$.

It is obvious from the results listed in Tables I-IV that if a desired accuracy is specified, then the minimum computational time is achieved by increasing the order of the splines rather than increasing the number of unknowns for a fixed order.

The results in Tables $V$ and VI show that our method is relatively stable with respect to experimental error which is of fundamental importance in most applications.

The numerical approaches used in [2] and [3] require knowledge of the reflection coefficient for values of frequency equal to $j \pi / 2$ for $j=1, \ldots, J$. Our method has no such restriction. In addition, accuracy comparable to that obtained by the above is achieved with far fewer reflection coefficient observations (typically, 2-4 times less).


Figs. 9-12. $k=3$.

The pulse spectrum technique (PST) used in [5] also avoids the above difficulties. However, due to the "analytic" solution of the initial value problem ( P ), and the overall simplicity of our method, it seems to be an attractive alternate to the PST.

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