A Source Localization Based on Signal Attenuation and Time Delay Estimation in Sensor Networks

H. Aghasi, M. Hashemi, and B. Hossein Khalaj

Abstract—**The problem of localization in sensor networks, based on both the time delays in signal reception and signal attenuation is considered in this paper. This approach would enhance the localization performance compared to when only phase shifts resulted by time delays or only attenuation information are used. Considering an attenuation model for the signal and taking into account the signal reception delays, a cost function minimization problem is formed. Due to the convergence speed, stability and the advantage of using trust region methods, a Levenberg-Marquardt algorithm is used to find the location of signal sources. Implementation details of the algorithm such as closed form equations to calculate the Jacobian at every iteration are also provided in this paper. At the end, some simulation results would demonstrate the validity of our proposed method**

Index Terms—**Levenberg marquardt algorithm, localization, wireless sensors**

I. Introduction

The vast development in integrated circuits technology offers the possibility of using low cost small sensors in large sensor networks. Sensors that are capable of communicating among themselves, either processing the data individually or through a central processing unit. The possibility of having sensors in different places, while still communicating as a network makes them a promising tool for challengingproblems such as localization/tracking of signal sources and particularly acoustic targets. In the past years, a lot of research is devoted to present methods of estimating the location of signal sources. Usually this localization is based on DOA estimation by processing the phase difference among receiving sensors [1], [2], measuring the time delay in receiving a signal at different sensors (particularly useful for wideband signals) [3], [4] and measuring the received energy of the signals at different locations [5]. For every category of methods, different processing algorithms are proposed. For DOA estimation of narrowband signals authors have proposed using multiple signal classification (MUSIC) [6] and maximum likelihood method (ML) [7]. For wideband signals two step algorithms of first estimating the time delays through methods such as cross correlation (CC) [8] or generalized cross correlation (GCC) [9] and then least square (LS) localization [10], [4] are proposed. For the same class of signals, Chen *et al.* in [11] proposed using an approximate maximum likelihood (AML) method capable of handling multiple targets when rather long samples of the signal are available. Localization based on the energy received at different sensors is also considered using methods such as maximum likelihood capable of handling multiple sources and projection onto convex sets [5], [12]. In the energy based methods usually the time delay in signal reception is ignored and based on a propagation model a priori known, localization is performed. In this paper, we tackle the problem of localization of multiple targets by using both the time delays in reception of the signals and the signal attenuation behavior. Our method generalizes the AML approach to coherently benefit the signal attenuation and provide a more robust algorithm, in which the targets should simultaneously satisfy the correct time delays among the sensors and provide sensible level of attenuation at each sensor. We use a basic model for the signal attenuation and based on that and considering the time delays, a maximum likelihood estimation problem is proposed. Compared to the traditional AML method, our proposed method is more robust and requires less number of samples due to the use of attenuation information. The paper is organized as follows. In Section II, we propose a general form for the received signal at every sensor and later discuss the signal attenuation model. In Section III, a maximum likelihood estimation of the source location is proposed. Due to stability, convergence speed and benefiting trust region methods, the Levenberg-Marquardt algorithm is considered for solving the resulting least squares minimization problem. Beside methods of implementing the algorithm, closed form equations for calculating the Jacobian are provided. In Section IV, we examine the efficiency of proposed method through some examples and finally there are some concluding remarks in Section V.

II. Problem Modeling

A. Modeling Received Signal

Consider N_T acoustic targets of unknown location r_{T_K}. At a time frame t, each source is omni-directionally emitting a signal $s_k(t)$, k≟? $\cdots, N_T$. Also N_S acoustic sensors are placed in known positions $r_{S_m}, m = 1, \ldots, N_S$, in the same environment. For every source in the environment, the function describing the signal attenuation at a point is $\alpha(\rho)$ where ρ the distance of that point to the source itself is. In general, the signal attenuation may be a function of many other parameters, such as the signal frequency, medium inhomogeneity, etc. For sake of simplicity, in this paper we

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consider it to be an identical form for all sources and solely a function of the distance to the source. With v being the propagation speed and considering $S_k(t\,?\,v)$ to be the signal of k^{th} source, measured 1 m away from that source, the total received signal from the acoustic sources at every sensor can be modeled as

$$x_m(t) = \sum_{k=1}^{N_T} \alpha\left(\rho_{m,k}\right) s_k\left(t - \tau_{m,k}\right) + w_m(t) \quad (1)$$

$$\text{for } t = 0, \dots, n_t - 1, \quad m = 1, \dots, N_s$$

where $\rho_{m,k} = \| r_{S_m} - r_{T_k} \|$ is the distance from k^{th} source to m^{th} sensor and $\tau_{m,k} = \rho_{m,k} / v$ is the corresponding time delay in signal reception. The received signal in (1) is normalized to each sensor gain, in order to reduce the number of notations. Moreover, the term $w_m(t)$ represents the background noise which is considered to be a zero mean white Gaussian with variance σ^2 for the purpose of this paper. Beside the positions r_{T_k} , which are the main unknowns of the localization problem, the waveform $s_k(t)$ are also unknown. The appearance of $\tau_{m,k}$ (which is related to the unknown quantitie r_{T_k})as the argument of an unknown waveform $s_k(t)$ may be problematic for any optimization scheme performed to solve the localization problem.

However this problem may be overcome through applying the discrete Fourier transform to (1) to extract the time delays $\tau_{m,k}$ and form an equivalent equation in which the unknown parameters are separated in individual terms, i.e.,

$$X_m(f) = \sum_{k=1}^{N_T} \alpha\left(\rho_{m,k}\right) exp\left(-\frac{j2\pi}{n_f} f \tau_{m,k}\right) S_k(f) + \xi_m(f)$$

$$\text{for } f = 0, \dots, n_f - 1, \quad m = 1, \dots, N_s \quad (2)$$

Here, $X_m(f)$, $S_k(f)$ and $\xi_m(f)$ are the data, signal and noise spectrums respectively. As stated in [11], we would like to highlight the fact that, for (2) to be a valid equivalent form of (1), we need n_t to be large enough to avoid edge effects and $n_f > n_t$. As we mentioned earlier, the attenuation information will help the algorithm overcome the drawbacks with the time-delay only consideration, however the signal length should still be long enough that the distortion caused by the edge effect does not overcome the compensation that modeling the attenuation causes.

B. Signal Attenuation Model

As discussed earlier, our assumption about the attenuation model in this paper is an identical model for all sources, which only depends on how far a point is located from the acoustic source. Based on (1), any signal attenuation model solely a function of ρ may be considered. However, for the purpose of this paper, we follow some recent energy based localization methods (e.g., see [5], [12]), in which the signal attenuation is considered to be inversely proportional to ρ or basically $\alpha(\rho) = \rho^{-1}$. This will be the attenuation model used to derive later equations in the paper, although with some slight modifications any other $\alpha(\rho)$ may be considered.

III. A Maximum Likelihood Estimation of the Unknowns

A. Derivation

Based on the attenuation model proposed, matching of the data spectrum with the model can be written as

$$X_m(f) = \sum_{k=1}^{N_T} \rho_{m,k}^{-1} exp\left(-\frac{j2\pi}{n_f} f \tau_{m,k}\right) S_k(f) + \xi_m(f) \quad (3)$$

Based on the central limit theorem $\xi_m(f)$, which is a transformed zero mean Gaussian random variable to the frequency domain, will be a complex zero mean Gaussian itself. For every frequency bin f having

$$\boldsymbol{X}(f) = \left[X_1(f), \cdots, X_{N_S}(f)\right]^T,$$

$$\boldsymbol{S}(f) = \left[S_1(f), \cdots, S_{N_T}(f)\right]^T$$

and $\boldsymbol{\xi}(f) = \left[\xi_1(f), \cdots, \xi_{N_S}(f)\right]^T$, (3) can be written in a matrix form as

$$\boldsymbol{X}(f) = \boldsymbol{\Phi}(f)\boldsymbol{S}(f) + \boldsymbol{\xi}(f) \quad (4)$$

where

$$\Phi(f) = \begin{pmatrix} \rho_{1,1}^{-1} e^{-j\frac{2\pi}{n_f v} f \rho_{1,1}} & \cdots & \rho_{1,N_T}^{-1} e^{-j\frac{2\pi}{n_f v} f \rho_{1,N_T}} \\ \vdots & \ddots & \vdots \\ \rho_{N_s,1}^{-1} e^{-j\frac{2\pi}{n_f v} f \rho_{N_s,1}} & \cdots & \rho_{N_s,N_T}^{-1} e^{-j\frac{2\pi}{n_f v} f \rho_{N_s,N_T}} \end{pmatrix} \quad (5)$$

The negative log-likelihood function to estimate the unknown parameters θ including the source positions, and source signal spectrums, is rewritable as

$$\theta = \operatorname{argmin} P^H P \quad (6)$$

where

$$P = \begin{pmatrix} P(0) \\ P(1) \\ \vdots \\ P(n_f - 1) \end{pmatrix} \quad (7)$$

and $\boldsymbol{P}(f) = \boldsymbol{X}(f) - \boldsymbol{\Phi}(f)\boldsymbol{S}(f)$. Similar to [11], based on the signal being real valued, we can only consider $n_f\,?2$

frequency bins and form $\hat{\boldsymbol{P}}$ with blocks of $P(f)$ for $f=1 \cdots n_f$. Moreover,(6) is equivalent to minimizing $P^H(f)P(f)$) for every f and considering the unknown signal spectrum $S(f)$ the minima should satisfy $\partial(\boldsymbol{P}^{\boldsymbol{H}}(f)\boldsymbol{P}(f))/\partial\boldsymbol{S}^{\boldsymbol{H}}(f)=0$ which leads to $\boldsymbol{S}(f)=\boldsymbol{\Phi}^{\dagger}(f)\boldsymbol{X}(f)$ with $\boldsymbol{\Phi}^{\dagger}(f)$ representing the pseudo-inverse of $\boldsymbol{\Phi}(f)$. Replacing the obtained $\boldsymbol{S}(f)$ in $\boldsymbol{P}(f)$, leads to a minimization, only in terms of the source locations, i.e. ,

$$r^*_{Tk} = argmin \hat{\boldsymbol{P}}^H \hat{\boldsymbol{P}} \tag{8}$$

where

$$\hat{\boldsymbol{P}}(f) = \mathbf{X}(f) - \mathbf{\Phi}(f)\boldsymbol{\Phi}^{\dagger}(f)\mathbf{X}(f) \tag{9}$$

$$f = 1 \cdots n_f$$

In the next section, we provide a method of tackling the nonlinear least squares minimization problem in (8).

1) A Levenberg-Marquardt Algorithm for the Minimization

For the purpose of minimizing the cost function in (8), we suggest using the Levenberg-Marquardt algorithm (LMA). Our attention towards this algorithm is based on two basic features. The first feature is its convergence properties. LMA is basically considered as a quasi-Newton method and provides a rather quadratic convergence, while being stabile [13]. The other feature of this method is benefiting from trust region methods [13]. In fact the cost function in (8) is not in general convex and may possess several local minima points. Using a trust region approach would be helpful in skipping some of the localities and with reasonable initial guesses; there would be a high chance of finding the global minimizer. For a 2D localization problem, as the scenarios in the example section, the vector of unknowns would be $\theta=[x^T{}_1,\ldots,x^T{}_{N_T},y_1^T,\ldots,y^T{}_{N_T}]^T$, where x_{T_k} and y_{T_k} are the x and y components of the position vector r_{T_k}. Clearly, the approach is not limited to 2D Cartesian systems and 3D Scenarios and other coordinate systems may be considered. For the LMA, which is an iterative algorithm we start with a $\theta(0)$ as the starting point, which usually contains the best guesses about the unknown values. At every iteration, having $\theta(n)$ already in hand $\theta(n+1)$ can be obtained by solving

$$\left(\boldsymbol{J}_{\theta}{}^{T}\boldsymbol{J}_{\theta}+\lambda^{(n)}\boldsymbol{I}\right)\left(\boldsymbol{\theta}^{(n+1)}-\boldsymbol{\theta}^{(n)}\right)=-\boldsymbol{J}_{\theta}{}^{T}\hat{\boldsymbol{P}} \tag{10}$$

where $\hat{\boldsymbol{P}}$ is the vertical vector of length $N_S n_f ?2$ explained in the previous section and obtained for values $\theta^{(n)}$ at that iteration. $\boldsymbol{J}_{\theta}$ is the Jacobian matrix of size $N_S n_f ?2 \times 2NT$. The parameter $\lambda^{(n)}$ is the damping factor, obtained at every iteration based on the trust region approach [14], [13]. In order to run the algorithm we need to know the Jacobian matrix at every iteration and the columns of the Jacobian matrix are obtained by having $\partial\hat{\boldsymbol{P}} / \partial x_{T_k}$ and $\partial\hat{\boldsymbol{P}} / \partial y_{T_k}$, closed forms of which are derived in the Appendix. In the next section, we will bring some examples to verify the validity of the method.

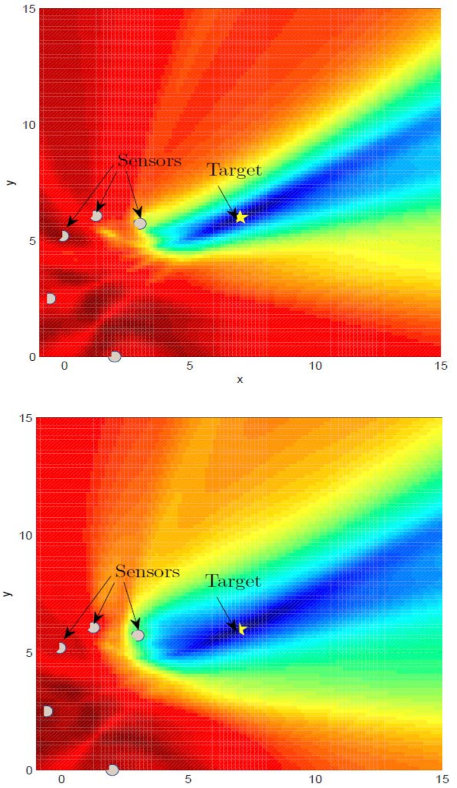

Fig. 1. The cost function corresponding to the traditional AML method (top) and our method (bottom). All numbers are in meters.

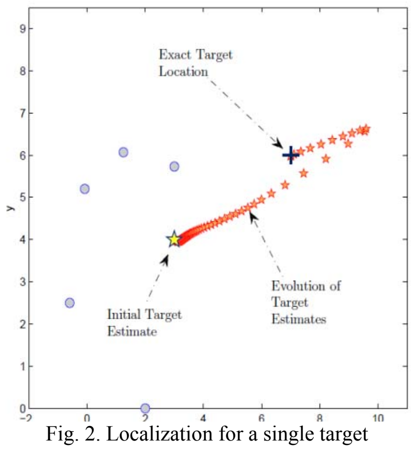

Fig. 2. Localization for a single target

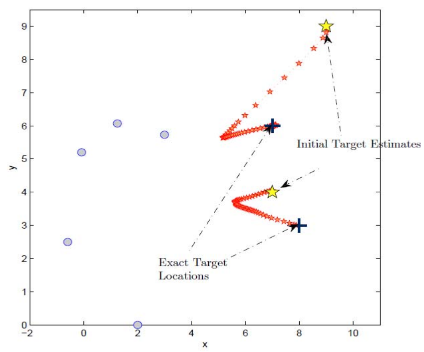

Fig. 3. Localization for two targets simultaneously

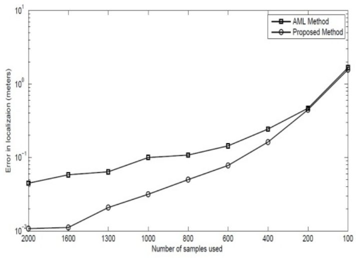

Fig. 4. The error caused by reducing the signal available samples for both AML and proposed method

IV. Simulation Results

In this section we provide some simulation results to show the performance of proposed method. As an example, we consider five sensors placed in the $x-y$ plane as shown in Fig. 1.

A wideband source with center frequency 500 Hz, and 200 Hz bandwidth located at point (7,6) is considered. The sampling frequency used is 4 KHz and $n_t = 1000$ samples are taken from the signal at every sensor. For the algorithm used n_f is taken to be 1050 and the SNR at every sensor is 15 dB. The propagation speed is the speed of sound as $v = 345$ m/s To provide a better understanding of the problem, we have shown the behavior of the cost function in the sensor-target area in Fig. 1. The top figure shows the cost function corresponding to the AML method in [11], where only time delays are considered and a normalized version of the signal is used. The bottom figure shows the cost function corresponding to our method.

One may observe that imposing the additional constraint of attenuation model has made the cost function smoother and less fluctuations and variations are observable. This is due to the fact that more parameters (time delay and amplitude vs time delay only in the AML method) are now involved in the cost function modeling and it is harder for two neighboring points to differ a lot with respect to both time delay and attenuation constraints and hence a smoother cost function is resulted. Also, since more information about the signal is used, the localization is improved whereas in this setting the AML cost function takes its minima at (6. 92 5. 94) while our cost function takes its minima at (6.99 5.97) which is a better estimate of the target.

For the purpose of performing the minimization using the LMA, we need to provide an initial target estimate. Finding good initial estimates of the target can be performed by using a course grid on the searching region. For the tracking problems, however, the localization results in previous time frames can be used as the initial estimates for the next frames. Despite this, we have initialized the problem from the point (3, 4) and as shown in Fig. 2, the algorithm was still able to move towards the global minimizer and reach the point (6.99, 5.97). The intermediate estimates of the target through the iterations are also shown in that figure. As a multiple target scenario, we consider the same problem setting as before with two targets located at (7, 6) and (8, 3). The initial estimates for the target positions were points (9, 9) and (7, 4). The resulting estimates of the target are shown in Fig. 3, for which the final results are (7.01, 5.98) and (7.89, 3.00), which are in good match with the true target locations. We also provide an experiment to examine the performance of proposed method. For this sake we use the single target example and start reducing the available samples at the sensors.

We always use $n_f = n_t + 50$ frequency bins, while reducing the collected signal samples from 2000 to 100 and observe the error occurred in target estimations. Fig. 4 shows the relationship between sampling points and the error in source estimates for both the AML and proposed method. The figure can well highlight the fact that for a certain number of signal samples available, using both time delays and attenuation information in the signal enhances the performance of the localization compared to the case that only time delays are used.

V. Conclusion

In this paper we proposed a method for localization of multiple acoustic wideband sources based on both signal attenuation and time delays in sensor networks. The method presented takes into account the signal attenuation behavior in the environment and as shown through simulations, provides a more appropriate cost function than that of the AML method. With the help of the attenuation model, less number of signal samples can be used to perform the localization compared to the case that only signal delays information is used. The minimization scheme used to solve the resulting nonlinear least square problem is the Levenberg-Marquardt, which uses trust region methods and less sensitive to local minima points.

Appendix: Jacobian Calculation

As mentioned earlier, in order to find columns of the Jacobian, we are required to find $\partial \hat{\boldsymbol{P}} / \partial \theta$, where θ is one of the unknown parameters x_{T_k} or y_{T_k}. Since $\hat{P}$ is a vector containing sub-vectors $\hat{\boldsymbol{P}}$ (f) for $f = 1 \cdots n_f$, we will only find $\partial \hat{\boldsymbol{P}}(f) / \partial \theta$ and clearly forming $\partial \hat{\boldsymbol{P}} / \partial \theta$ would be aligning the corresponding sub-vectors.

From (9) we have

$$\partial \hat{\boldsymbol{P}}(f) / \partial \theta = -\frac{\partial}{\partial \theta} (\boldsymbol{\Phi}(f) \boldsymbol{\Phi}^{\dagger}(f) \boldsymbol{X}(f)). \quad (11)$$

For sake of simplicity in notations and avoiding the appearance of the frequency bin f in all the derivations we denote $\boldsymbol{\Psi} = \boldsymbol{\Phi}(f)$ and so expanding (11) yields

$$\frac{\partial \hat{\boldsymbol{P}}(f)}{\partial \theta} = -(\frac{\partial \boldsymbol{\Psi}}{\partial \theta} \boldsymbol{\Psi}^{\dagger} + \boldsymbol{\Psi} \frac{\partial \boldsymbol{\Psi}^{\dagger}}{\partial \theta}) \boldsymbol{X}(f) \quad (12)$$

We first consider finding $\frac{\partial \boldsymbol{\Psi}^{\dagger}}{\partial \theta}$. Referring to Section III, $\boldsymbol{\Psi}^{\dagger}$ is simply calculated through $\boldsymbol{\Psi}^{\dagger} = (\boldsymbol{\Psi}^H \boldsymbol{\Psi})^{-1} \boldsymbol{\Psi}^H$ or in other words

$$(\boldsymbol{\Psi}^{H}\boldsymbol{\Psi}\ \boldsymbol{\Psi}^{\dagger}=\boldsymbol{\Psi}^{H} \qquad (13)$$

Taking a derivative from both sides of (13) results

$$\frac{\partial(\boldsymbol{\Psi}^{H}\boldsymbol{\Psi}}{\partial\theta}\boldsymbol{\Psi}^{\dagger}+(\boldsymbol{\Psi}^{H}\boldsymbol{\Psi}\ \frac{\partial\boldsymbol{\Psi}^{\dagger}}{\partial\theta}=\frac{\partial\boldsymbol{\Psi}^{H}}{\partial\theta}$$

or

$$\frac{\partial(\boldsymbol{\Psi}^{H}\boldsymbol{\Psi}}{\partial\theta}\boldsymbol{\Psi}^{\dagger}+(\boldsymbol{\Psi}^{H}\boldsymbol{\Psi}\ \frac{\partial\boldsymbol{\Psi}^{\dagger}}{\partial\theta}=\frac{\partial\boldsymbol{\Psi}^{H}}{\partial\theta}$$

which result in

$$\frac{\partial\boldsymbol{\Psi}^{H}}{\partial\theta}\boldsymbol{\Psi}\boldsymbol{\Psi}^{\dagger}+\boldsymbol{\Psi}^{H}\frac{\partial\boldsymbol{\Psi}}{\partial\theta}\boldsymbol{\Psi}^{\dagger}+\boldsymbol{\Psi}^{H}\boldsymbol{\Psi}\frac{\partial\boldsymbol{\Psi}^{\dagger}}{\partial\theta}=\frac{\partial\boldsymbol{\Psi}^{H}}{\partial\theta} \qquad (14)$$

Using (14) in (12) and recalling $\boldsymbol{\Psi}^{\dagger H}=\boldsymbol{\Psi}\ \boldsymbol{\Psi}^{H}\boldsymbol{\Psi}^{-}$, would result

$$\frac{\partial\hat{\boldsymbol{P}}(f)}{\partial\theta}=-\left(\frac{\partial\boldsymbol{\Psi}}{\partial\theta}\boldsymbol{\Psi}^{\dagger}+\boldsymbol{\Psi}^{\dagger H}\left(\frac{\partial\boldsymbol{\Psi}^{H}}{\partial\theta}\left(\boldsymbol{I}-\boldsymbol{\Psi}\boldsymbol{\Psi}^{H}\right)-\boldsymbol{\Psi}^{H}\frac{\partial\boldsymbol{\Psi}}{\partial\theta}\boldsymbol{\Psi}^{\dagger}\right)\right)\boldsymbol{X}(f \qquad (15)$$

which can be written as

$$\frac{\partial\hat{\boldsymbol{P}}(f)}{\partial\theta}=\left(\left(\boldsymbol{I}-\boldsymbol{\Psi}^{\dagger H}\boldsymbol{\Psi}^{H}\right)\frac{\partial\boldsymbol{\Psi}}{\partial\theta}\boldsymbol{\Psi}^{\dagger}+\boldsymbol{\Psi}^{\dagger H}\frac{\partial\boldsymbol{\Psi}^{H}}{\partial\theta}\left(\boldsymbol{I}-\boldsymbol{\Psi}\boldsymbol{\Psi}^{\dagger}\right)\right)\boldsymbol{X}(f)=\left\{\Gamma+\Gamma^{H}\right\}\boldsymbol{X}(f)$$

where

$$\Gamma=\left(\boldsymbol{\Psi}^{\dagger H}\boldsymbol{\Psi}^{H}-\boldsymbol{I}\right)\frac{\partial\boldsymbol{\Psi}}{\partial\theta}\boldsymbol{\Psi}^{\dagger}$$

Now that we have a closed form for calculation of the Jacobian columns, we can specifically discuss finding $\frac{\partial\boldsymbol{\Psi}}{\partial\theta}$ Because of similar forms, here we only discuss $\frac{\partial\boldsymbol{\Psi}}{\partial x_{T_k}}$ .Simply taking a derivative with respect to x_{T_k} in (5) shows that the (m,k) element of $\frac{\partial\boldsymbol{\Psi}}{\partial x_{T_k}}$ is related to the (m,k) element of $\boldsymbol{\Psi}$ through

$$\left[\frac{\partial\boldsymbol{\Psi}}{\partial x_{T_{k'}}}\right]_{m,k}=\delta\left(k,k'\right)\frac{x_{S_m}-x_{T_k}}{\rho_{m,k}}\left(\frac{1}{\rho_{m,k}}+\frac{j2\pi f}{n_f v}\right)\left[\boldsymbol{\Psi}\right]_{m,k}$$

where

$$\delta\left(k,k'\right)=\begin{cases}1; k=k'\\0; k\neq k'\end{cases}$$

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