An Efficient Algorithm for Estimating the Signal-to-Interference Ratio in TDMA Cellular Systems

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ABSTRACT

A new algorithm is proposed for estimating the signal-to-interference ratio (SIR) in TDMA cellular systems. The proposed SIR estimator is evaluated for use in the IS-54/136 system and a GSM-like system, and compared with existing SIR estimation algorithms. Our results show that the proposed algorithm has better performance than existing algorithms in terms of the mean square prediction error. When the computational requirements are considered, the proposed algorithm has far less computational complexity than existing algorithms of comparable performance.
Keywords: SIR estimation, computational complexity.

1. Introduction

Many of the radio resource management algorithms used in first generation macrocellular systems employed received signal plus interference plus noise power (S+I+N) as a measure of radio link quality. This approach works well for such macrocellular systems, because the radio propagation environment is fairly predictable and the required signal-to-interference plus noise ratio, S/(I+N), of first generation systems is fairly large. However, these conditions will no longer be true for future microcellular systems, where the propagation environment is characteristically erratic and the radio receivers are designed to operate at a much lower S/(I+N). For these systems, a radio link having large (S+I+N) may be deprived of good quality because of a correspondingly low S/(I+N). Consequently, S/(I+N) is considered to be a key parameter for the more contemporary cellular radio resource management algorithms for handoffs [1], dynamic channel assignment [2, 3], and power control [4]. Many of these algorithms operate under the premise that fast and accurate measurements of the received S/(I+N) are available at either the base stations (BSs), mobile stations (BSs), or both.

Several methods have been recently proposed for TDMA cellular systems, to generate accurate, real time, estimates of the received S/(I+N). One such method has been suggested by Austin and Stüber [5] that uses the training and/or color code sequences that are typically present within each TDMA slot to obtain an unbiased estimate of the S/(I+N). The numerical examples in [5] show that the S/(I+N) can be estimated to within 2 dB in less than a second for an IS-54/136 system. The signal-to-variance (SVR) power estimator proposed in [6] is another method. This method uses the autocorrelation sequence of the received signal samples for a short time scale. The application of SVR method to a DECT system reveals that the estimator suffers from a large bias for interesting values of S/I. Another S/I estimation algorithm for TDMA cellular systems has been reported in [7]. The algorithm uses the eigenvalues of the covariance matrix of the received signal sequence to estimate the S/I. Simulation results for a GSM-like system show that the S/I can be estimated within an error of 0.3 dB in 200 ms. The method has, however, some computational burden.

This paper develops a new and efficient S/(I+N) estimation method for TDMA cellular systems. The method has low computational complexity and a lower average absolute prediction error than all of the S/(I+N) estimation algorithms discussed above. The remainder of the paper is organized as follows. Section 2 presents the discrete-time framework for the channel model and signal quality estimation, and presents the basic idea of the proposed estimation technique. Computational issues are discussed in Section 3. Section 4 summarizes the simulation results for the proposed SIR estimation technique. Finally, Section 5 provides some concluding remarks.

2. Discrete-Time Channel Model

Following [5], the overall discrete-time channel consisting of the transmit filter, channel, matched filter, and baud-rate sampler and can be modeled as an M-tap, T-spaced, transversal filter, where T is the baud duration. The overall channel taps can be described by the vector $\mathbf{f} = [f_1, \ldots, f_M]^T$. The received samples y_n at the output of the matched filter have the form

$$y_n = \sum_{k=1}^{M} a_{n-k} f_k + w_n, \tag{1}$$

where $\{a_n\}$ is the transmitted symbol sequence and the w_n are samples of the received interference plus noise. Let $\mathbf{y} = [y_1, \ldots, y_L]^T$ be a length L vector of received samples. It follows that the received signal vector $\mathbf{y}$ is

$$\mathbf{y} = \mathbf{A}\mathbf{f} + \mathbf{w}, \tag{2}$$

where $\mathbf{A}$ is an $L \times M$ Toeplitz matrix consisting of the transmitted symbols of the form

$$\mathbf{A} = \begin{bmatrix} a_0 & a_{-1} & \cdots & a_{1-M} \\ a_1 & a_0 & \cdots & a_{2-M} \\ \vdots & \vdots & \ddots & \vdots \\ a_L & a_{L-1} & \cdots & a_{L-M} \end{bmatrix}. \tag{3}$$

and $\mathbf{w} = [w_1, \ldots, w_L]^T$ is the vector of received interference plus noise samples. The matrix $\mathbf{A}$ is commonly called a *convolution* *matrix*. If there are N_I interfering BSs, then $\mathbf{w}$ can be expressed as

$$\mathbf{w} = \sum_{k=1}^{N_I} \mathbf{A}_k \mathbf{f}_k + \mathbf{n}, \quad (4)$$

where $\mathbf{n}$ is a zero-mean, discrete-time, white Gaussian process. Since the BSs are unsynchronized in TDMA cellular systems such as IS-54/136, PDC, and GSM, the received signal sample sequences from the interfering BSs can be considered as uncorrelated and mutually uncorrelated. This implies that $\mathbf{w}$ and $\mathbf{A}$ are mutually uncorrelated. Furthermore, it is reasonable to assume that the channel taps, $\mathbf{f}$, are uncorrelated with both the symbol sequence $\{a_k\}$ and the interference plus noise vector $\mathbf{w}$. Assuming a zero-mean signal constellation, it follows that $\mathbf{y}$ and $\mathbf{w}$ are zero-mean uncorrelated random processes.

The received signal plus interference plus noise power, and the received interference plus noise power, are $\sigma_S^2 = \frac{1}{L}\mathrm{E}[\mathbf{y}^H\mathbf{y}]$ and $\sigma_{I+N}^2 = \frac{1}{L}\mathrm{E}[\mathbf{w}^H\mathbf{w}]$, respectively. Assuming ergodicity, the ensemble averages can be replaced time-averages so as to obtain the unbiased estimates of S and I+N, denoted by $\hat{\sigma}_S^2$ and $\hat{\sigma}_{I+N}^2$, respectively. That is

$$\hat{\sigma}_S^2 = \frac{1}{L}\mathbf{y}^H\mathbf{y} \qquad \hat{\sigma}_{I+N}^2 = \frac{1}{L}\mathbf{w}^H\mathbf{w}. \quad (5)$$

2.1 Estimating (I+N)

Suppose that $\mathbf{A}$ has more rows than columns, i.e., $L > M$. Let $\mathcal{R}(\mathbf{A})$ and $\mathcal{N}(\mathbf{A})$ denote the range space and null space of $\mathbf{A}$, respectively, where $\mathcal{R}(\mathbf{A})$ and $\mathcal{N}(\mathbf{A})$ are defined with respect to the *left eigenvectors*. Also, let $Q = \dim(\mathcal{R}(\mathbf{A}))$ and $P = \dim(\mathcal{N}(\mathbf{A}))$. Then $Q + P = L$, $Q \le M$ and $P \ge L - M$. Let $\{\mathbf{e}_1, \ldots, \mathbf{e}_P\}$ be the orthonormal basis for $\mathcal{N}(\mathbf{A})$ and $\{\mathbf{e}_{P+1}, \ldots, \mathbf{e}_L\}$ be the orthonormal basis for $\mathcal{R}(\mathbf{A})$. Since $\mathcal{N}(\mathbf{A}) = \mathcal{R}(\mathbf{A})^\perp$, there exists a unique $\mathbf{x} \in \mathcal{N}(\mathbf{A})$ and $\mathbf{z} \in \mathcal{R}(\mathbf{A})$ such that $\mathbf{w} = \mathbf{x} + \mathbf{z}$, where $\mathbf{x}$ is the orthogonal projection of $\mathbf{w}$ onto $\mathcal{N}(\mathbf{A})$. We can express $\mathbf{x}$ as

$$\mathbf{x} = \sum_{i=1}^{P} \mathbf{e}_i \langle \mathbf{e}_i, \mathbf{w} \rangle, \quad (6)$$

where $\langle \cdot, \cdot \rangle$ denotes the inner product and $\langle \mathbf{x}, \mathbf{w} \rangle = \mathbf{x}^H\mathbf{w}$. From *Bessel's inequality*

$$\|\mathbf{x}\|^2 = \sum_{i=1}^{P} |\langle \mathbf{e}_i, \mathbf{w} \rangle|^2 \le \|\mathbf{w}\|^2, \quad (7)$$

where $\|\mathbf{x}\|^2 = \langle \mathbf{x}, \mathbf{x} \rangle = \mathbf{x}^H\mathbf{x}$. Now consider

$$\begin{aligned} \mathrm{E}[\mathbf{x}^H\mathbf{x}] \equiv \mathrm{E}[\|\mathbf{x}\|^2] &= \mathrm{E}[\sum_{i=1}^{P} |\langle \mathbf{e}_i, \mathbf{w} \rangle|^2] \\ &= \sum_{i=1}^{P} \mathrm{E}[|\langle \mathbf{e}_i, \mathbf{w} \rangle|^2]. \end{aligned} \quad (8)$$

However,

$$\begin{aligned} \mathrm{E}[|\langle \mathbf{e}_i, \mathbf{w} \rangle|^2] &= \mathrm{E}[\sum_{j=1}^{L} e_{i,j} w_j \sum_{k=1}^{L} e_{i,k}^* w_k^*] \\ &= \mathrm{E}[\sum_{j=1}^{L}\sum_{k=1}^{L} e_{i,j} e_{i,k}^* w_j w_k^*] \\ &= \sum_{j=1}^{L}\sum_{k=1}^{L} e_{i,j} e_{i,k}^* \mathrm{E}[w_j w_k^*] \\ &= \sum_{j=1}^{L} |e_{i,j}|^2 \sigma_w^2 = \sigma_w^2 \end{aligned} \quad (9)$$

where the second last equality follows from the fact that $\mathrm{E}[w_j w_k^*] = 0$ for $j \ne k$, as shown in [5]. Combining (8) and (9)

$$\sigma_w^2 = \frac{1}{P}\mathrm{E}[\mathbf{x}^H\mathbf{x}] \ . \quad (10)$$

Replacing the ensemble average in (10) with time-averaging yields the unbiased estimate

$$\hat{\sigma}_w^2 = \frac{1}{P}\mathbf{x}^H\mathbf{x} = \frac{1}{P}\sum_{i=1}^{P} |\langle \mathbf{e}_i, \mathbf{w} \rangle|^2 \ . \quad (11)$$

This effectively forms the time-average of P samples of $\mathbf{w}$. To improve the estimate of $\hat{\sigma}_w^2$, it is desirable that L be as large as possible so that we have larger P to average the most samples (*law of large numbers*).

Since $\mathbf{e}_i \in \mathcal{N}(\mathbf{A}),\ i = 1, \ldots, P$

$$\langle \mathbf{e}_i, \mathbf{y} \rangle = \langle \mathbf{e}_i, \mathbf{A}\mathbf{f} + \mathbf{w} \rangle = \mathbf{e}_i^H\mathbf{A}\mathbf{f} + \mathbf{e}_i^H\mathbf{w} = \mathbf{e}_i^H\mathbf{w} = \langle \mathbf{e}_i, \mathbf{w} \rangle. \quad (12)$$

Hence, $\langle \mathbf{e}_i, \mathbf{w} \rangle = \langle \mathbf{e}_i, \mathbf{y} \rangle\ \forall\ \mathbf{e}_i \in \mathcal{N}(\mathbf{A})$. Also, note that $\hat{\sigma}_w^2$ and $\hat{\sigma}_{I+N}^2$ are the same quantity. Therefore,

$$\hat{\sigma}_{I+N} = \frac{1}{P}\sum_{i=1}^{P} |\langle \mathbf{e}_i, \mathbf{y} \rangle|^2 \ . \quad (13)$$

2.2 Estimating S/(I+N)

After obtaining an estimate for the interference plus noise power, S/(I+N) can be estimated if the signal power can be separated from the interference plus noise power. The signal plus interference plus noise power is

$$\begin{aligned} \sigma_{S+I+N}^2 &= \frac{1}{L}\mathrm{E}[\mathbf{y}^H\mathbf{y}] \\ &= \frac{1}{L}\mathrm{E}[\mathbf{f}^H\mathbf{A}^H\mathbf{A}\mathbf{f} + \mathbf{w}^H\mathbf{w}] \\ &= \frac{1}{L}\mathrm{E}[\mathbf{f}^H\mathbf{A}^H\mathbf{A}\mathbf{f}] + \sigma_{I+N}^2, \end{aligned} \quad (14)$$

where the second equality follows from the assumption that $\mathbf{w}$ is zero-mean and uncorrelated with $\mathbf{A}$ and $\mathbf{f}$. The first term in (14) is the signal power, σ_S^2. Hence, an SIR estimator can easily be formed by

$$\widehat{\mathrm{SIR}} = \left(\frac{\hat{\sigma}_{S+I+N}^2}{\hat{\sigma}_{I+N}^2} - 1\right) = \frac{\hat{\sigma}_S^2}{\hat{\sigma}_{I+N}^2}, \quad (15)$$

where $\hat{\sigma}_{S+I+N}^2$ is obtained by replacing ensemble average in (14) with a time-average, i.e., $\hat{\sigma}_{S+I+N}^2 = \frac{1}{L}\mathbf{y}^H\mathbf{y}$. When (15) is combined with (13), the SIR estimator becomes

$$\widehat{\mathrm{SIR}} = \frac{\frac{1}{L}\mathbf{y}^H\mathbf{y}}{\frac{1}{P}\sum_{i=1}^{P} |\langle \mathbf{e}_i, \mathbf{y} \rangle|^2} - 1 \ . \quad (16)$$

Finally, if (I+N) and (S+I+N) are estimated for N different input vectors, then (16) has the more general form

$$\widehat{\mathrm{SIR}} = \frac{\sum_{i=1}^{N} \mathbf{y}_i^H\mathbf{y}_i}{\sum_{i=1}^{N} \frac{L}{P_i}\sum_{k=1}^{P_i} |\langle \mathbf{e}_k^i, \mathbf{y} \rangle|^2} - 1 \ . \quad (17)$$

3. Computational Issues

As mentioned earlier a fast and accurate estimate of (I+N) requires that $\mathcal{N}(\mathbf{A})$ be as large as possible. Assume that $\{\mathbf{c}_1, \ldots, \mathbf{c}_P\}$ is the basis for $\mathcal{N}(\mathbf{A})$ found by Gaussian elimination. To obtain an orthonormal basis for $\mathcal{N}(\mathbf{A})$, we need to orthonormalize $\{\mathbf{c}_1, \ldots, \mathbf{c}_P\}$. This orthonormalization can be computationally intensive, because we try to choose P as large as possible to obtain a better estimate of $\hat{\sigma}^2_{I+N}$. The number of floating point multiplications and additions required for this orthonormalization process is proportional to P^2.

Instead of projecting $\mathbf{y}$ onto $\mathcal{N}(\mathbf{A})$, we can project it onto $\mathcal{R}(\mathbf{A})$. We can uniquely write $\mathbf{y} = \mathbf{x} + \mathbf{v}$, where $\mathbf{x} \in \mathcal{N}(\mathbf{A})$ and $\mathbf{v} \in \mathcal{R}(\mathbf{A})$. Then, we have

$$\|\mathbf{y}\|^2 = \|\mathbf{x}\|^2 + \|\mathbf{v}\|^2 \tag{18}$$

by the *Pythagorean Theorem*. Also, observe that $\mathbf{w} = \mathbf{x} + \mathbf{z}$, where $\mathbf{x} \in \mathcal{N}(\mathbf{A})$ and $\mathbf{z} \in \mathcal{R}(\mathbf{A})$, since the projection of $\mathbf{w}$ and $\mathbf{y}$ onto $\mathcal{N}(\mathbf{A})$ are the same. By using the projection of $\mathbf{v}$ onto $\mathcal{N}(\mathbf{A})$ and (18), $\|\mathbf{x}\|^2$ can be expressed as

$$\|\mathbf{x}\|^2 = \|\mathbf{y}\|^2 - \sum_{i=P+1}^{L} |\langle \mathbf{e}_i, \mathbf{y} \rangle|^2 \ . \tag{19}$$

Hence, the SIR estimate can be obtained as

$$\begin{aligned}
\widehat{\mathrm{SIR}} &= \frac{\sum_{i=1}^{N} \|\mathbf{y}_i\|^2}{\sum_{i=1}^{N} \frac{L}{P_i}\|\mathbf{x}_i\|^2} - 1 \\
&= \frac{\sum_{i=1}^{N} \|\mathbf{y}_i\|^2}{\sum_{i=1}^{N} \frac{L}{P_i}(\|\mathbf{y}_i\|^2 - \|\mathbf{v}_i\|^2)} - 1 \\
&= \frac{\sum_{i=1}^{N} \|\mathbf{y}_i\|^2}{\sum_{i=1}^{N} \frac{L}{L-Q_i}(\|\mathbf{y}_i\|^2 - \sum_{k=P_i+1}^{L} |\langle \mathbf{e}^i_k, \mathbf{y}_i \rangle|^2)} - 1
\end{aligned} \tag{20}$$

We do the above modifications because it is computationally easier to obtain an orthonormal basis for $\mathcal{R}(\mathbf{A})$ than $\mathcal{N}(\mathbf{A})$. Actually, the columns of $\mathbf{A}$ are readily available as a basis for $\mathcal{R}(\mathbf{A})$. The columns of $\mathbf{A}$ have to be orthonormalized by using *Gram-Schmidt* process to obtain an orthonormal basis for $\mathcal{R}(\mathbf{A})$. The computational complexity of this orthonormalization procedure is determined by the number of columns of $\mathbf{A}$, yielding M^2L multiplications and $\frac{1}{2}M(M+1)L$ additions. Hence, a significant computational saving is realized by chosing $P = \dim(\mathcal{N}(\mathbf{A}))$ as large as possible, i.e., we choose L as large as possible relative to M.

4. Training Sequence Based Signal Quality Estimation

The analysis to this point has assumed that all received symbol sequences are known. In practice, only the training and colour code sequences are known in each TDMA burst. These known sequences will be used to construct the convolution matrix $\mathbf{A}$ described in the above analysis. We now determine the performance of the proposed S/(I+N) estimator, using only the training and colour code sequences in IS-54/136 and GSM-like systems. These sequences are used for BS and sector identification, symbol sychronization, sample timing, and channel estimation.

The next section compares the performance of the proposed SIR estimation algorithm with existing SIR estimation algorithms. The final form of the SIR estimator in (20) projects the received signal vectors are onto the signal subspace. Hence, the proposed algorithm is called *Signal Projection* (SP). In [7], the SIR estimation method proposed by Austin and Stüber [5] is called the *Interference Projection* (IP) method, and the SIR estimation method proposed in [7] is called the *Subspace Based* (SB) SIR estimator. These names will be used in the sequel.

4.1 Simulation Results

The performance of the (I+N) and S/(I+N) estimators, developed in the previous section, were tested through the software simulation for both an IS-54/136 system [8] and a GSM-like system. With IS-54/136, $\pi/4$-DQPSK modulation is used with a symbol rate of 24.3 ks/s. Each frame has 6 bursts of 162 symbols, as shown in Fig. 1, where each burst has a duration of 6.67 ms. Here we assume that a MS has correctly determined its serving BS (meaning that the colour code is known) and is operating in half-rate mode (meaning that it receives one burst per frame). Consequently, in each frame the 14-symbol training sequence and 6-symbol colour code sequences are known.

The GSM system uses Gaussian minimum shift keying (GMSK) with a raw bit rate of 270.8 kb/s. Each frame has 8 slots and each burst contains 148 symbols with a 26-symbol training sequence located in middle of the burst, for a burst duration of 0.577 ms as shown in Fig. 2. For simplicity we define a GSM-like system that replaces GMSK with BPSK, but otherwise has has the same frame structure as GSM. Our simulations assume a two-equal-ray, baud-spaced, Rayleigh fading channel with uncorrelated taps for both the IS-54/136 and GSM-like systems. It is not important to use the same channel model for both systems, because our intention is not to make comparisons between systems. Rather, we wish to assess the relative performance of the SIR estimators when they are applied to each system.

1) IS-54/136 System: For the IS-54/136 system, two cases are examined; one uses the training sequences only and the other uses both the training and colour code sequences. From the training sequence, a 13×2 Toeplitz matrix is obtained. Additive white Gaussian noise at 20 dB below the interference power was also included. In all the simulations the true S/I is 5 dB, and the same experiment was run 500 times (with a different seed) with the results averaged to obtain a good approximation for mean SIR estimation error $\mathrm{E}[|\mathrm{S/I} - \widehat{\mathrm{SIR}}|]$.

Figs. 3 and 4 plot the mean absolute SIR estimation error against the averaging time for the SP, IP and, SB estimators for one and 6 co-channel interferers, respectively. Fig. 3 shows that IP performs poorly compared to SP and SB for all MS speeds. SB has very large initial SIR estimation errors in the order of 100 dB (not shown), but later converges and is almost as good as SP. The SIR can be estimated with SP to within an average error of 0.5 dB at 100 km/h and 1 dB at 5 km/h. Comparison of Figs. 3 and 4 shows that all the SIR estimators perform slightly better when the number of interferers increases. Although not shown, the performance of the SIR estimators were found to be insensive to the true S/I.

One may think that the 6-symbol colour code could improve the performance of the estimation algorithm. SP estimation was performed with 6-symbol colour code in addition to the 14 symbol training sequence. The simulation results are shown in Fig. 5 which makes comparisions with the first case where the colour code was not used. The colour code does not provide any significant improvement because, in this case, $L = 5$ and $P = 3$ which are not large enough to improve the SIR estimate.

2) GSM System: Figs. 6 and 7 show the mean absolute SIR estimation error against the averaging time for the SP and SB estimators. The SP estimator is seen to perform slightly better than SB estimator. As before, the SB estimator has very large mean error at the beginning (not shown), but begins to converge after four or five bursts. Figs. 6 and 7 show that the SIR can be estimated within an average error of 0.3 dB at 100 km/h after 300 ms and 1 dB at 5 km/h after one second.

4.1.1 Computational complexity of SP vs SB

Although the SP and SB estimators have similar performance, the real benefit of SP is its computational efficiency. As mentioned in Section III, SP requires M^2L multiplications and $\frac{1}{2}M(M+1)L$ additions for each estimate. On the other hand, SB requires the eigenvalues of an $L \times L$ Hermitian matrix, L different values of a sphericity test fuction, together with a search algorithm for a vector of length L. Finding the eigenvalues of a matrix is computationally intensive. As described in [9], the QR algorithm is the most efficient and widely used method to calculate the eigenvalues of a matrix. Basically, the QR algorithm is an iterative procedure where the covariance matrix, $\mathbf{B}$, is factored as $\mathbf{B} = \mathbf{QR}$ with $\mathbf{R}$ upper triangular and $\mathbf{Q}$ orthogonal. The iteration continues with $\mathbf{B}_m = \mathbf{Q}_m\mathbf{R}_m$ and $\mathbf{B}_{m+1} = \mathbf{R}_m\mathbf{Q}_m$, where $\mathbf{B}_1 = \mathbf{B}$. The sequence $\{\mathbf{B}_m\}$ will converge to a triangular matrix with the eigenvalues of $\mathbf{B}$ on its diagonal. Each iteration of the QR algorithm requires $O(L)$ multiplications and additions for a tridiagonal matrix. A symmetric matrix can be transformed to a *Hessenberg* (tridiagonal in this case) matrix with a cost of $O(L^3)$ multiplications and additions.

The number of iterations required in the QR algorithm depends on the eigenvalues of the matrix. The convergence properties of the QR method are discussed in [9]. The following theorem is taken from [9].

Theorem 1 *Let $\mathbf{B}$ be a real matrix of order n, and let its eigenvalues $\{\lambda_i\}$ satisfy*

$$|\lambda_1| > |\lambda_2| \cdots > |\lambda_n| > 0. \tag{21}$$

Then iterates $\mathbf{R}_m$ of the QR method will converge to an upper triangular matrix $\mathbf{D}$, which contains the eigenvalues $\{\lambda_i\}$ in the diagonal positions. If $\mathbf{B}$ is symmetric, the sequence $\{\mathbf{B}_m\}$ converges to a diagonal matrix. For the speed of convergence,

$$\|\mathbf{D} - \mathbf{B}_m\| \le c \max_i \left| \frac{\lambda_{i+1}}{\lambda_i} \right|. \tag{22}$$

The covariance matrix used in SB algorithm (theoretically) has the following eigenvalues

$$\lambda_i = \begin{cases} \sigma_{S_i}^2 + \sigma_{I+N}^2 & \text{if } i = 1, \ldots, Q \\ \sigma_{I+N}^2 & \text{otherwise} \end{cases} \tag{23}$$

as described in [7]. In the simulations $M = 2$ and $Q \le M$, and $L = 13$. Hence, $\max_i |\lambda_{i+1}/\lambda_i| = 1$, which implies that the algorithm convergences very slowly. Actually, the number $\max_i |\lambda_{i+1}/\lambda_i|$ is not 1, but close to 1, in the simulations. In our simulation of SB algorithm, the number of floating point operations (flops[1]) was calculated for the eigenvalue computation of each covariance matrix without balancing. The average number of flops is obtained afterwards, which is 106000 flops. This is considerably large number compared to $M^2L = 52$ flops needed for the SP method.

5. Concluding Remarks

A computationally simple and fast estimation technique was developed to estimate S/(I+N) in TDMA wireless systems that employ known sequences of training symbols. The performance of the new estimator was evaluated for various situations through software simulations. The proposed estimation technique outperforms all other known techniques in the literature with respect to both accuracy and computational complexity.

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[1] One flop is one floating point multiplication and one floating point addition.

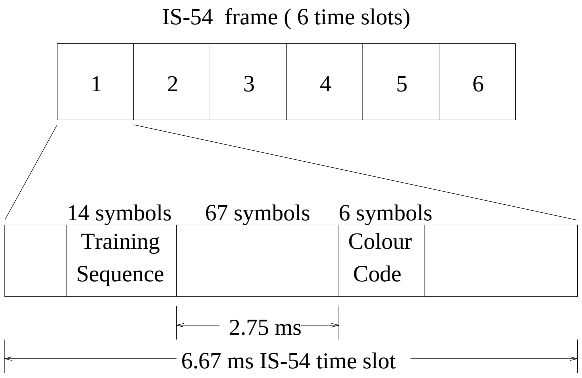

Figure 1: IS-54 frame structure showing the relative locations of the training and colour code sequences (not to scale).

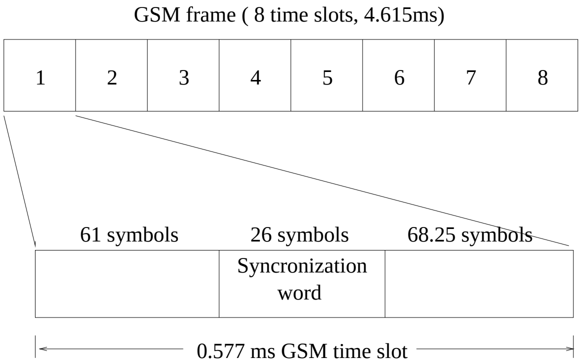

Figure 2: GSM frame structure showing the relative location of the training sequence (not to scale).

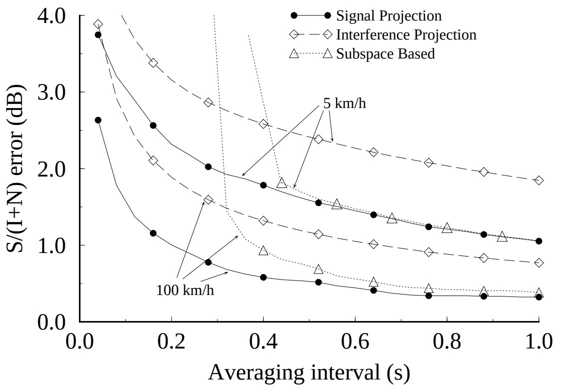

Figure 3: Mean SIR estimation error against the averaging time; $N_I = 1$ and S/I=5 dB.

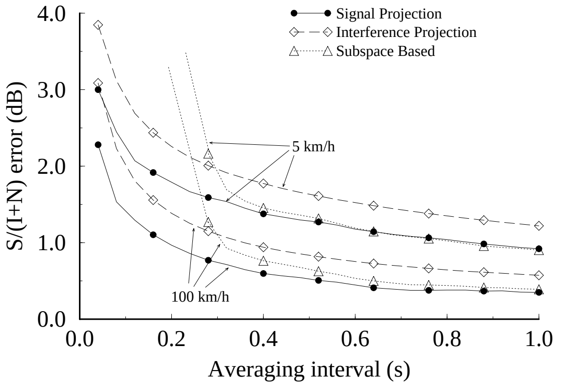

Figure 4: Mean SIR estimation error against the averaging time; $N_I = 6$ and S/I=5 dB.

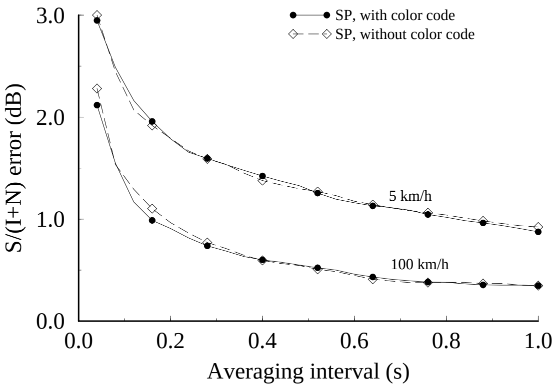

Figure 5: Mean SIR estimation error against the averaging time; $N_I = 6$ and S/I=5 dB.

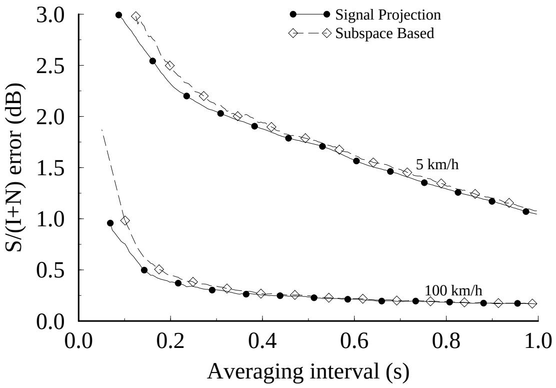

Figure 6: Mean SIR estimation error against the averaging time; $N_I = 1$ and S/I=5 dB.

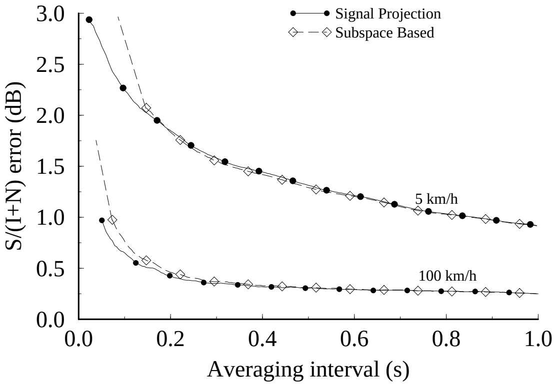

Figure 7: Mean SIR estimation error against the averaging time; $N_I = 6$ and S/I=5 dB.