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Research Article

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Study on Compressed Sensing Sparse Channel Based on Bayesian Estimate in Wireless Sensor Networks

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ABSTRACT

Actual measurements have shown that in many cases, the wireless channel is a channel with sparse. In order to use the bayesian channel estimation algorithm to estimate channel, using sparse characteristic of the channel at the same time, the paper improved the search method of support set in SABMP algorithm .In the process of dominate search support set introduces the ideas of viterbi decoding path, eventually reduce the computational complexity of the algorithm. Theoretical analysis and simulation results verify the effectiveness of the improved algorithm.

Key words: wireless sensor networks; Bayesian estimation; compressed sensing; greedy algorithm

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INTRODUCTION

The traditional channel model was generally supposed that channel vector of each element is subject to independent identically distributed random variables, it is generally believed to obey Gaussian distribution, but look from actual observations, in many cases show a sparse characteristics of wireless channel is channel vector elements of value is very small, can approximate to zero. For sparse channel estimation problem is currently a hot research topic in the field of communications. Compressed sensing algorithm can make full use of the sparse characteristics of the channel, can obtain superior than the traditional least squares (LS) method estimates of performance, at the same time also does not have a lot of increase their algorithm complexity. Compressed sensing principle of estimation is to estimate the signal projection onto random observation matrix, by the sparse observation vector to estimate target signal [1].Bayesian channel estimation algorithm is also a kind of traditional estimation algorithm, Bayesian estimation to estimate the channel with channel mathematical expectation, the estimation error is minimal. To the sparse characteristic of channel, is used to calculate the mathematical expectation of random variable, can be a few can ignore small probability event, leaving some big probability event, to take advantage of bayesian estimation algorithm, to calculate the relative probability of each major event, target was calculated by the relative probability to the expectation of a random variable. If enough small had probability events, the difference between the two estimates can be ignored. In literature [2] a Bayesian channel estimation algorithm is proposed and is called DABMP algorithm, the algorithm of channel does not require the distribution of random variables can be used for any distribution channel estimation. Thesis on the basis of the original algorithm, an improved algorithm to keep the original algorithm of random variable distribution, on the basis of wide adaptability [3-4], the selection of big probability event has made the improvement, by setting a threshold, will be much fewer big probability events are preserved, and improve the search to the actual the possibility of a big probability event set, so as to improve the performance of channel estimation. Paper compares the improved algorithm and DABMP algorithm performance; the simulation results verify the effectiveness of the improved algorithm [5-8].

SPARSE CHANNEL MODEL

Channel model in reference [2], a sparse channel model can be represented as:

$$h=h_a*h_b \quad (1)$$

H is a channel vector, *N* long is the product of had award, ha is of length *N*, obey a certain distribution of random variables, h_b is the vector of length N, each of these elements are independent identically distributed variables, and obey the parameters for the Bernoulli distribution of *P*. In order to reflect the sparse nature of channel, there are many zero elements in *h*, so *P* values smaller [9-10].

If the pilot signal transmitter launch, pilot signal matrix with a Gaussian random variable signal matrix, has related literature prove Gaussian probability matrix is very satisfy RIP (Restricted Isometry Property) properties [3] [4].Observations of the observation vector y can be expressed as:

$$y=\phi h+n \qquad (2)$$

Formulas of ϕ is M*N observation matrix, the launch of the pilot signal can be understood as a matrix, *n* is subject to a plural additive white Gaussian noise of Gaussian distribution. Based on compressed sensing theory, as long as h enough sparse, then use a dimension is small, the observation vector can be restored dimension vector h, namely can do M*N.

According to the theory of probability knowledge, the mathematical expectation of h Africa zero position number is NP [11-13]. Channel vector h in the zero position number and nearly equal to the probability of NP relatively large. So please mathematical expectation when these things to consider. The above analysis is based on the prior probability distribution of the conclusion, after receiving the pilot signal response situations happening probability and changed [14-15]. An estimate of signal under test is to use mathematical expectation instead of the estimated signal expression can be expressed as follows:

$$\hat{h}_{mmse} = E[h/y] = \sum_{s} p(s/y)E[h/y,s] \qquad (3)$$

The $E[h/y,s]=(\Phi_s^H\Phi_s)^{-1}\Phi_s^H y$ is expressed as received *y* and know the location under the premise of the non-zero channel's expectations, use pseudo-inverse matrix multiplied by the observation vector *y* instead of $E[h/y,s]=(\Phi_s^H\Phi_s)^{-1}\Phi_s^H y$;Said the expectations in premise for received *y* channel's is support set, namely the zero set position.

For any support set, the denominator is *p*(*y*), to compare the time can be neglected. *P*(*s*) is the prior probability, obey the Bernoulli distribution. Key is *p*(*y*/*s*), *y* is on ϕ by h projection and additive Gaussian white noise, and Gaussian distribution is a superimposed on a non-Gaussian variable, if remove non Gaussian component, will get a Gaussian distribution of the variables. Therefore the y projections to ϕ orthogonal complementary space are:

$$\Phi s^{\dagger}\ y = \Phi s^{\dagger}\ n \qquad (4)$$

$\Phi s^{\dagger}$ is Φs orthogonal complement matrix here.CC to obey Gaussian distribution. Ignore some subtle influence and the probability of the exponential, the resulting in literature [2] the size of a probability measure is:

$$\begin{aligned} v(s) &= \ln p(y/s)p(s) \\ &= \frac{1}{2\sigma_n^2}\left\|\Phi_s(\Phi_s^H\Phi_s)^{-1}\Phi_s^H y\right\|^2 - \frac{1}{2\sigma_n^2}\|y\|^2 + |s|\ln p + (N-|s|)\ln(1-P) \end{aligned} \qquad (5)$$

SUPPORT SET SEARCH ALGORITHM

The mathematical expectation of a random variables depends on the value and any possible to get the corresponding probability. Approximately equal the average probability of event probability. A length of the sequence of *N*, and each position on the numerical had zero and not two kinds of circumstances. There are 2^n the sequence. Non-zero position number expectation is NP, so the number of non-zero probability should be near the NP in location number than other non-zero probability. From 2^N case to find the maximum probability of NP a non-zero position, need to search for $\binom{N}{NP}$ AA, when *N* is large, too large amount of calculation. Literature [2] is a reduce amount of calculation algorithm, first search the first nonzero position, need to search for $\binom{N}{1}$, search the second position, and then on the basis of the need to search the $\binom{N-1}{1}$, and so on, until you find the location of the all. *N*=60, for example, p=0.05, it is necessary to search for NP=3 non-zero position, adopts full search, need to search the $\binom{60}{3}$=34220, and use simple algorithm only need to search 177 case.

But at the time of every search, the first big probability and may be very small compared to the probability that the second big difference, and that there is a lot of probability search to the wrong results. That is in front of the search results as long as there is one step wrong, the end result would not be right. In order to reduce the happening of this kind of situation, the literature [2] rounds of search, search in the first round to the column position assumed POS1, when the first position for the second round of the search will exclude POS1, search in the position of the remaining set. This adds to the search of computation. In order to solve this problem, the thesis applies the ideas of the viterbi decoding path to search process. Sparse channel length is N, every position with zero and not two kinds of state, each state may be regarded as the 0 s and 1 s of binary code. If not considering channel vector elements of specific values, channel estimation is to long for N binary code. All search is corresponding to the path of the path length is N decoding, SABMP algorithm is quite so the path of the path length of 1 decoding. The longer the path length, had decoding the more accurate, the greater the algorithm complexity. In order to both equilibrium and path length is set to 2.And the probability of two paths only when the difference is small to decode with path length 2, if the difference is very big decoding is used by position.

Searches for the first position, the position of each non-zero probability from big to small order, compare the first and the second number, if the ratio of the first and second values greater than the threshold, can retain maximum probability corresponds to the location, otherwise keep corresponding to the location of the two probabilities. Searches for the second and subsequent position, if there are two locations to retain the last time, it respectively on the basis of their reserve position search add position, and then put all the probability from big to small order, to determine whether the ratio of the two largest probability is greater than the threshold th, more than just keep two kinds of circumstances, otherwise, they only keep a situation. And then calculates retained the relative probability of all cases, finally calculate the approximate mathematical expectation.

Procedure G(Φ,y,p,σ_n^2,pos)

Initialize L←{1,2,…,N}, i←1

Initialize empty sets Smax,sd,p(sd/y),E[x/y,sd]

Li←L

While i$\leq$pos do

Ω←{smax$\cup${α1}, smax$\cup${α2}, …smax$\cup${α|Li|}|$\alpha k\in$ Li

Compute {$\nu(s_k)$ | $s_k \in \Omega$

$\nu(s_{1*}) \geq$ maxj $\nu(s_j)$, $\nu(s_{2*}) \geq$ maxj{ $\nu(s_j) \setminus \nu(s_{1*})$ }

If $\frac{\nu(s_{1*})}{\nu(s_{2*})} \geq th$

sd←{sd, s1*}

Compute {p(s1*/y),E[x/y,s1*)}

P(sd/y) ← { P(sd/y), P(s1*/y)}

E[x/y,sd] ← { E[x/y,sd], E[x/y,s1*]}

smax←s1*

Li+1←L\s1*

i←i+1

else

Sd1←{sd, s1*}, Sd2←{sd, s2*}

Compute {p(s1*/y),E[x/y,s1*)}, {p(s2*/y),E[x/y,s2*)}

P(sd1/y) ← { P(sd/y), P(s1*/y)}, P(sd2/y) ← { P(sd/y), P(s2*/y)}

E[x/y,sd1]←{E[x/y,sd],E[x/y,s1*]},E[x/y,sd2]←{E[x/y,sd], E[x/y,s2*]}

smax1←s1*,smax2←s2*

L1,i+1←L\s1*, L2,i+1←L\s2*

i←i+1

End if

End while

Return sd1, P(sd1/y), E[x/y,sd1]

End procedure

SIMULATION AND EVALUTION

Simulation parameter Settings are as follows: channel length *N*=256, number *M*=64 observations, the sparse degree of P_1=0.05, the signal-to-noise ratio of 20 db, SABMP *D*=10 cycles in the algorithm, the improved algorithm cycles *D*=1.The simulation result of both methods is shown in figure 1:

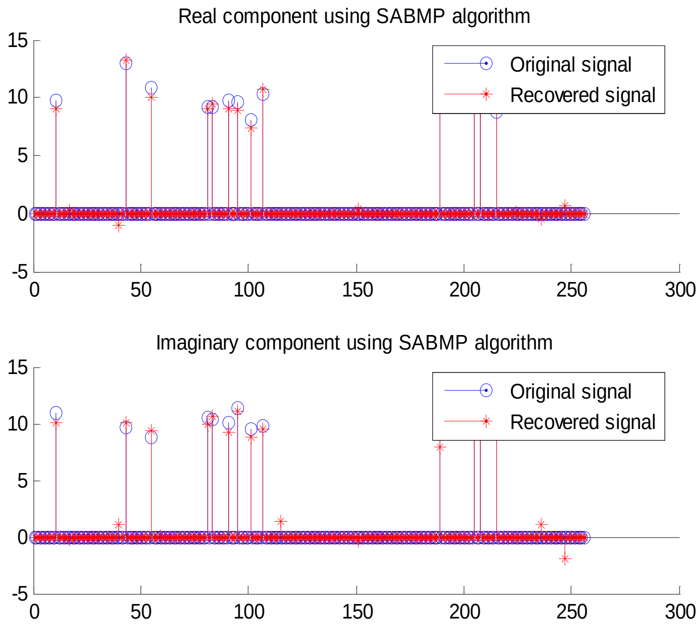

Fig.1 (a): *t*=50s, Two algorithms to restore signal error performance comparison

Seen from the simulation results of two kinds of algorithm can restore the original signal very well.Calculated under two kinds of algorithm to estimate the signal and original signal mean square error (mse) is 19.56 dB and 20.18 dB, respectively, the differences between the two is very small, and because of the improved algorithm cycles is one over ten of the original, the computation is reduced greatly.

CONCLUSION

This article mainly elaborated based on pilot symbol aided channel estimation, the first detailed introduction based on pilot assisted LS, MMSE channel estimation algorithm, and in the Matlab simulation platform of LS, MMSE channel estimation are compared, and the simulation Although the MMSE channel estimation performance is better, but in the solving process to compute inverse matrix, increase the computational complexity, right In some high real-time demand system, MMSE is generally not used; LS algorithm is simple, and don't have to know first. Check information, better estimation performance, so to be able to use a wide range of; finally based on the LS channel estimation algorithm for noise sensitivity. The shortcomings of feeling, by adopting wavelet packet to the LS algorithm to estimate the channel response value for noise reduction processing, optimized the LS. Channel estimation algorithm, the simulation results show that the improved LS channel estimation effectively reduce noise to estimate the channel response value make the LS channel estimation algorithm, the influence of the performance got obvious improvement.

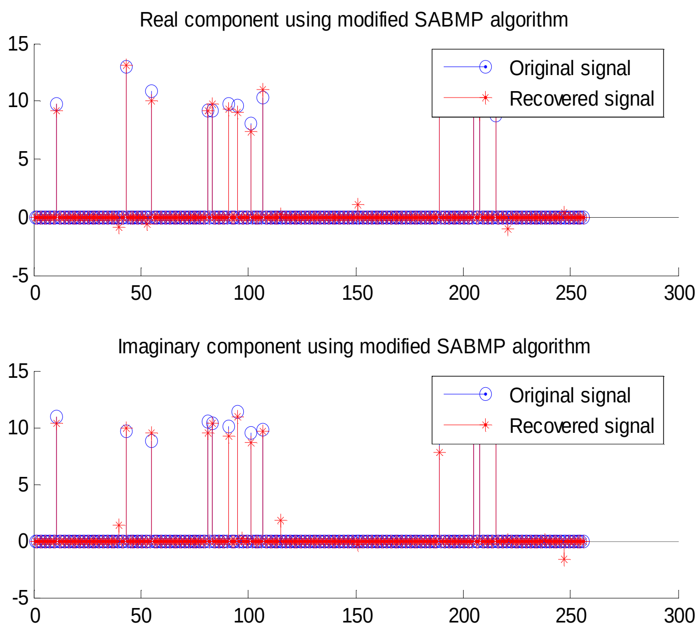

Fig.1(b):*t*=100s, Two algorithms to restore signal error performance comparison

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REFERENCES

[1] Donoho, D. *IEEE Trans. Inf. Theory* ,v.52,n.2, pp.1289-1306,**2006**.

[2] Masood, M, Al-Naffouri, T. *IEEE Trans. Signal Process*,v.61,n.12, pp 5298-5309, **2013**

[3] Hiroki H, Marco H. Ryuji K. *Vehicular Technology Conference*, pp.1-5, **2006**

[4]Abbas K. *The International Arab Journal of Information Technology*, v.9,n.3,pp.225-234, **2012**.

[5] Yu X, Zhang X, Bi G. *Communications, IEEE Proceedings*, v151,n.2,pp.152-156,**2014**.

[6] Fasih.D, Sobia B, Mughal, J. *World Applied Science Journal*, v.20, n.7, pp.1008-1013,**2012.**

[7] Antony J. *Wireless Communications and Mobile Computing Journal*, v.5,n.2,pp.1-18, **2015.**

[8] Zhang Y, Cheng S. *IEEE Trans Power Deliv*, v.19,n.4,pp.1668-1672,**2004.**

[9] X. Xu, X. Wei, and Z. Ye. *IEEE Signal Process. Lett*., v. 19, n. 3, pp. 155–158, **2012**.

[10] X. Wei, Y. Yuan, and Q. Ling, *IEEE Trans. Signal Process*., v. 60,n. 12, pp. 6382–6394, **2012**.

[11] B. Farhang-Boroujeny, *IEEE Signal Process. Mag*., v. 28, n. 3, pp. 92–112, **2011**.

[12] L. Vangelista and N. Laurenti, *IEEE Trans. Commun*., v. 49, n. 4, pp. 664–675, **2001**.

[13] P. Siohan, C. Siclet, and N. Lacaille, *IEEE Trans. Signal Process*., v. 50, n. 5, pp. 1170–1183, **2002**.

[14] T. Fusco and M. Tanda, *IEEE Trans. Signal Process.*, vol. 55, no. 5, pp. 1828–1838, **2007**.

[15] X. Li, P. Wan,. *IEEE Transactions on Computers*, v.52,n.6,pp.1293-1307,**2003**.