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Research Article

A Bayesian Algorithm of Wireless Sensor Network Link Selection under Asymmetric Loss Function

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Abstract: Traditional link selection algorithms of wireless sensor networks needs lots of data packages as testing samples and the nodes of wireless sensor networks are battery-powered. Then it is a shortcoming for the limited energy of wireless sensor networks. The aim of this study is to propose new link selection algorithms to overcome this shortcoming based the concept of Bayesian approach. The new Bayesian link selection algorithms are derived under an asymmetric loss function. Finally, simulations are performed to compare the performance of the new method with other methods. The simulations show that the new algorithm has a good adaptability.

Keywords: Asymmetric loss function, Bayesian link selection algorithm, wireless sensor networks

INTRODUCTION

Wireless Sensor Network (WSN) has been widely applied various fields, such as wireless data transmission of a greenhouse environment data acquisition system, power supply system and plant growth environmental information monitoring system (Lihong*et al*., 2014; Wang, 2014; Zhang *et al*., 2014). Link selection algorithm of WSN is an important topic in WSN field. Many traditional link selection algorithms (empirical-algorithms) are put forward (Hou*et al*., 2007; Zhu *et al*., 2008; Shu *et al*., 2013). But the energy of nodes of WSN is limited and they need to send many data packets as testing samples, which is a contradiction for the limited energy in WSNs.

Bayesian algorithm is a good alternative for small test samples. Zhang *et al*. (2009) proposed a Bayesian link selection method of WSN based on non-information prior distribution under squared error loss function. Luo *et al*. (2012) developed Bayesian and hierarchical Bayesian link selection method of WSN under squared error loss function. Luo and Ren (2014) developed link selection algorithms of wireless sensor networks based on expect Bayesian algorithms. These Bayesian algorithm work well.

But in Bayesian estimation, an important element isthe selection of a loss function, noted by$L(\hat{\boldsymbol{\theta}},\theta)$, where $\hat{\boldsymbol{\theta}}$is a decision rule based on the data. The Squared Error Loss (SEL) function as the most common symmetric loss function is widely used due to its great analysis properties. SEL function is a symmetrical loss function that assigns equal losses to overestimation and underestimation. However, in many practical problems, Basu and Ebrahimi (1992) pointed that overestimation and underestimation will make different consequents. Thus using of the symmetric loss functions may be inappropriate and to overcome this difficulty, many asymmetric loss functions are put forward. Then this study will proposed a new Bayesian link selection algorithm under a asymmetric loss function. The new algorithm is proposed on the basis of a non-information prior distribution and Beta prior distribution under a precautionary loss function.

PRELIMINARY KNOWLEDGE

In this section, we will recall some concepts of Bayesian estimation and some preliminaries knowledge. Bayesian approach is an important statistical technique, which has many applications in various fields, such as model selection (Huttunen and Tohka, 2015), image denoising algorithm (Sun *et al*., 2014), reliability analysis (Han, 2011), medical diagnosis (Yet *et al*., 2014) and queuing theory (Ren and Wang, 2012).

In the Bayesian analysis process, loss function and prior distribution are two important elements for Bayesian statistics analysis. In this study, we suppose the prior distributions of the parameter$\theta$are uniform distribution and Beta distribution respectively.

These two prior distributions are induced as follows:

- The probability density function (pdf) of quasi-prior distribution is defined as:

$$\pi_1(\theta;d) \propto \frac{1}{\theta^d}, \quad \theta > 0, d > 0 \tag{1}$$

Hence, $d = 0$ leads to a diffuse prior and $d = 1$ to a non-informative prior.

- The pdf of Beta distribution, noted by $Beta(\alpha, \beta)$, is defined as follows:

$$\pi_2(\theta; \alpha, \beta) = \frac{1}{B(\alpha, \beta)} \theta^{\alpha-1}(1-\theta)^{\beta-1} \tag{2}$$

where $\alpha > 0, \beta > 0$ are two hyper parameters.

The asymmetric loss function used in this study is given as follows (Norstorm, 1996):

$$L(\hat{\theta}, \theta) = \frac{(\hat{\theta} - \theta)^2}{\hat{\theta}} \tag{3}$$

where, $\hat{\theta}$ is a estimator of θ.

The loss function(3) infinitely nears to the origin to preventunderestimation, thus giving conservative estimators, especially when low failure rates are being estimator. It is very useful when underestimation may lead to serious consequences.

The Bayes estimator under precautionary loss function (3) is denoted by $\hat{\theta}_B$ can be derived as:

$$\hat{\theta}_B = [E(\theta^2 \mid X)]^{1/2} \tag{4}$$

Lemma 1: Supposed that the parameter θ is a random variable and it is regarded as the success rate (packet received rate) of a link. Then under the squared error loss function $L(\hat{\theta},\theta) = (\hat{\theta}, \theta)^2$, we have the following conclusion (Zhao andKulasekera, 2009; Luo *et al*., 2012):

- When the prior distribution of θ is uniform distribution, the Bayesian estimation of parameter θ is:

$$\hat{\theta}_{B1} = \frac{x+1}{n+2} \tag{5}$$

- When the prior distribution of θ is Beta(α, β), the Bayesian estimation of parameter θis:

$$\hat{\theta}_{B2} = \frac{\alpha + x}{n + \alpha + \beta} \tag{6}$$

Here the parameter n is the number of data package which be sent form the source node of a link, parameter x is the number of data package which be received successfully by the destination node of the same link.

Asymmetric bayesian algorithm of link selection of WSN: In this section, we will give the new link selection algorithm under assymmetric loss functions.

Theorem 1: Supposed that the parameter θ is a random variable and it is regarded as the success rate (packet received rate) of a link. Then under the precautionary loss function (3), when the prior distribution of θ is quasi-prior distribution, then the Bayesian estimation of parameter θ is:

$$\hat{\theta}_{AB1} = \left[\frac{(x-d+2)(x-d+1)}{(n-d+3)(n-d+2)} \right]^{1/2} \tag{7}$$

Proof: We consider the case when the prior density ofθ is quasi-prior (1), then the likelihood function is combined with the prior by using the Bayes theorem to obtain the posterior density:

$$\begin{aligned} h(\theta \mid x) &\propto p(x \mid \theta)\pi_1(\theta; d) \\ &\propto \binom{n}{x} \theta^x (1-\theta)^{n-x} \frac{1}{\theta^d} \\ &\propto \theta^{x-d}(1-\theta)^{n-x} \end{aligned} \tag{8}$$

It is obvious that the random variable θ |X is distributed with Beta distribution $Beta(x-d+1, n-x+1)$ .Then, under the precautionary loss (3), the Bayes estimator of θ is:

$$\begin{aligned} \hat{\theta}_1 &= [E(\theta^2 \mid X]^{1/2} = [\int_0^1 \theta^2 h_1(\theta \mid X) d\theta]^{1/2} \\ &= \frac{\int_0^1 \theta^2 \cdot \theta^{x-d}(1-\theta)^{n-x} d\theta}{\int_0^1 \theta^{x-d}(1-\theta)^{n-x} d\rho} = \left[\frac{(x-d+2)(x-d+1)}{(n-d+3)(n-d+2)} \right]^{1/2} \end{aligned}$$

Theorem 2: Supposed that the parameter θ is a random variable and it is regarded as the success rate (packet received rate) of a link. Then under the precautionary loss function (3), when the prior distribution of θ is Beta(α, β), the Bayesian estimation of parameter θ is:

$$\hat{\theta}_{AB2} = \left[\frac{(\alpha + x + 1)(\alpha + x)}{(\alpha + \beta + n + 1)(\alpha + \beta + n)} \right]^{1/2} \tag{9}$$

Proof: The likelihood function is combined with the Beta prior distribution (2) by using the Bayes theorem to obtain the posterior density:

$$\begin{aligned} h(\theta \mid x) &\propto p(x \mid \theta)\pi_2(\theta; \alpha, \beta) \\ &\propto \binom{n}{x} \theta^x (1-\theta)^{n-x} \frac{1}{\beta(\alpha, \beta)} \theta^{\alpha-1}(1-\theta)^{\beta-1} \\ &\propto \theta^{\alpha+x-1}(1-\beta)^{\beta+n-x-1} \end{aligned} \tag{10}$$

It is obvious that $\theta \mid X$ is distributed with Beta distribution $Beta(\alpha + x, \beta + n - x)$. Then, under the precautionary loss (3), the Bayes estimator of $\theta$is:

Table 1: The values of each algorithm for estimating two links' quality

	Lower link quality				Preferable link-quality			
Link-quality (n,x)	(10,8)	(20, 16)	(30, 21)	(100,70)	(10, 9)	(20, 19)	(30, 28)	(100, 90)
$\hat{\theta}_G$	0.8000	0.8000	0.7000	0.7000	0.9000	0.9500	0.9333	0.9500
$\hat{\theta}_{B1}$	0.7500	0.7727	0.6875	0.6961	0.8333	0.9091	0.9063	0.9412
$\hat{\theta}_{B2}$ (α=0.5, β=1.0)	0.7391	0.7674	0.6825	0.6946	0.8261	0.9070	0.9048	0.9409
$\hat{\theta}_{B2}$ (α=1.0, β=1.5)	0.7200	0.7556	0.6769	0.6927	0.8000	0.8889	0.8923	0.9366
$\hat{\theta}_{AB1}$ (d=0)	0.7596	0.7777	0.6922	0.6976	0.8397	0.9111	0.9077	0.9415
$\hat{\theta}_{AB1}$ (d=1)	0.6290	0.7020	0.6417	0.6812	0.7032	0.8297	0.8507	0.9227
$\hat{\theta}_{AB1}$ (d=2)	0.5164	0.6325	0.5941	0.6651	0.5855	0.7550	0.7971	0.9043
$\hat{\theta}_{AB2}$(α=0.5, β=1.0)	0.7495	0.7726	0.6874	0.6961	0.8330	0.9090	0.9062	0.9412
$\hat{\theta}_{AB2}$(α=0.5, β=1.0)	0.7303	0.7607	0.6817	0.6942	0.8074	0.8912	0.8939	0.9369

$$\hat{\theta}_2 = [E(\theta^2 \mid X]^{1/2} = [\int_0^1 \theta^2 h_2(\theta \mid X) d\theta]^{1/2} = \frac{\int_0^1 \theta^2 \cdot \theta^{\alpha+x-1}(1-\theta)^{\beta+n-x-1} d\theta}{\int_0^1 \theta^{\alpha+x-1}(1-\theta)^{\beta+n-x-1} d\theta}$$

$$= \left[\frac{(\alpha+x+1)(\alpha+x)}{(\alpha+\beta+n+1)(\alpha+\beta+n)} \right]^{1/2}$$

A simulation example: To test the performance of the new induced Bayesian algorithms ($\hat{\theta}_{AB1}$and $\hat{\theta}_{AB2}$), a simulation experiment under the data (n, x) of network environment is performed. Two link-qualities: lower link-quality and preferable link-quality are considered. We estimate the quality of different links; in which$\hat{\theta}_{AB2}$ and$\hat{\theta}_{AB2}$is relative to hyper parameter (α, β) = (0.5, 1.0), (1.0, 1.5), $\hat{\theta}_{AB1}$ is relative to hyper parameter d = 0, 1 and 2. We took many groups of observations with different values of pair (n, x). The computing results of each algorithm for estimating two links' quality are reported in Table 1.

We use$\hat{\theta}_G$as the estimated value of empirical-algorithms and$\hat{\theta}_G$= x/n, but the credibility of value of $\hat{\theta}_G$must rely on great samples. It can be analyzed from Table 1 that the value of$\hat{\theta}_{B1}$, $\hat{\theta}_{B2}$, $\hat{\theta}_{AB1}$ and$\hat{\theta}_{AB2}$can get more better estimates than that of empirical-algorithms, especially when n is small. All the algorithms approach to the actual value with the increasing of size n. Therefore, using Bayesian algorithms to estimate the quality of links are superior to empirical-algorithms.

CONCLUSION

This study designed a new link-selection algorithms of WSN based on Bayesian method under a asymmetric loss function named a precautionary loss function. We cansee that the Bayesian algorithms have higher success rate than empirical-algorithms in selecting the high-quality link under the conditions of small samples. Among these algorithms, the Bayesian algorithms under asymmetric loss can include the attitude of decision maker, which have superior than Bayesian algorithms under squared error loss function. Simulations proved that the new Bayesian algorithms have good adaptability and can get better experimental results. In summary, the Bayesian algorithms can be treated as a useful alternative reference for links-selection of WSN.

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