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Research Article

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The WSN prediction algorithm of real flow based on ARMA model and wavelet transform

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ABSTRACT

To improve the prediction accuracy of real flow in wireless network, a new prediction algorithm, state prediction algorithm was proposed basing on ARMA model and Wavelet Transform(SPWA). In this algorithm, first defined distribution character and theoretical foundation of ARMA model, then yielded higher real flow prediction accuracy basing combined predictions of ARMA and wavelet transform. at least, simulations were conducted to study the key factor of algorithm through OPNET and MATLAB. The results show that, comparing to FARIMA model and MF-FIR model, SPWA has better suitability.

Key words: Prediction accuracy; ARMA ; Wavelet; character

INTRODUCTION

Wireless sensor network(WSN) grows rapidly from its birth[1-5]. Meanwhile, network jam is more and more concerned because it thresholds the quality of WSN. Some researchers proposed some solutions to eliminate the jam, CODA[6], fusion[7] suggested to control the jam by adjusting the network knots and flow. These two are concerning how to do it during the jam, however, if the jam can be forecasted and then erased before it happened, that will be effectively and efficiently improve the wireless network quality. So how to control real flow and then predict the flow state becomes the key issue. there are some classic network prediction methods like AR, ARMA and FARIMA. Other models such as wavelets transform and chaos model also introduced to real flow prediction. Wei Shan and his colleagues [8] improved ARMA model with super linear convergence of variable metric method and proposed real flow prediction methods based on autocorrelation coefficients and partial autocorrelation coefficients tailing methods. Based on optimized IPSO, Yang Song et al., [9] prolonged searching time of the initial stage and final stage of the iteration to balance entire searching and local searching, and then to optimize model parameters to construct a chaos supporting vector machine model. Hsianghsi Wen et al., studied an optimized sample online fuzzy predicting method via least squares support vector machine and fuzzy LSSVM training, also they studied characters of real flow over time and long period [10]. To improve the high risk Dandan Li et al., successfully improved the prediction accuracy by constructing the Back Propagation network value method through combined wavelet and ant colony algorithm towards traditional predicting method high risk on training data [11]. Chao Li et al., improved logistic model with cosine function, and then depicted state evolution and the chaotic character of real flow using nonlinear time sequence analysis and logistic model [12]. Ting Lei et al., introduced wavelet decomposed the flow time sequence and yielded wavelet transform scaling coefficient sequence and wavelet coefficient sequence, and then taking coefficient sequence as well as original flow time sequence as input and output for the model to construct an artificial neural network to train [13]. Meiying Ye et al., constructed a online fuzzy least squares support vector for real-time updating predicting accuracy but which also effected by time scale [14].

In this paper, a new algorithm for real flow is proposed which can predict by combing ARMA model and wavelet transform with less error, the effectiveness of the algorithm can be verified by mathematical simulation. The first part shows the characters of ARMA model, in the second part shows the judgement foundation of the ARMA and constructs predicting algorithm, in the third part runs simulating on OPNET and MATLAB, and finally a conclusion.

1. ARMA Model

ARMA is known as its high predicting accuracy, realtime and effectiveness. In wireless sensor, a normal flow sequence is: $W_1, W_2, \ldots W_t$, can be written as:

$$W_t = \sum_{i=1}^{p} \tau_1 W_{t-i} - \sum_{j=1}^{q} \rho_j a_{t-j} + a_t \tag{1}$$

where $a_t \in N(0, \sigma_a^2)$,τ_i, ρ_i are coefficients, a_t is distract. Eq.(1) presents a p order autoregressive moving average model over m order, can be written as ARMA(p,q), in which p and q are the order indicators of AR and MA respectively. τ_i(i=1,2,…, p) and ρ_i (j=1,2,…, q) are model parameters for each part. Here expectation of W_t for E(W_t) is:

$$E(W_t) = \sum_{i=1}^{n} \tau_t W_{t-i} - \sum_{j=1}^{m} \rho_j a_{t-j} \tag{2}$$

E(W_t) is effected by W_{t-i} and a_{t-j}. Define after moving operator B, so BW_t=W_{t-1} can be rewritten as:

$$W_t = (\tau_1 B - \tau_2 B^2 - \cdots - \tau_p B^p) W_t + \alpha_t \tag{3}$$

so q order moving average date can be represented as:

$$W_t = (\rho_1 B - \rho_2 B^2 - \cdots - \rho_q B^q) \alpha_t \tag{4}$$

So the autoregression model of stationary random process ARMA(p,q) is:

$$\begin{cases} \tau_p(B) W_t = \rho_q(B) \alpha_t \\ \tau_p(B) = 1 - \tau_1 B - \tau_2 B^2 - \cdots \tau_P B^P \\ \rho_q(B) = 1 - \rho_1 B - \rho_2 B - \cdots \rho_q B^q \end{cases} \tag{5}$$

take p=2, q=1 for less computing burden, and employ least square to evaluate the model, where the principle of least square is:

$$J = \sum_{i=1}^{N} (Y_i - \hat{Y}_i)^2 = \sum_{i=1}^{N} (Y_i - a_0 - a_1 W_i)^2 \tag{6}$$

where Y_i is the ith observation value of Y, Wi is the ith observation value of W. α_0 is intercept and α_1 is slope. taking J partial derivative with respect to α_0 and α_1 can get:

$$\begin{cases} \dfrac{\partial J}{\partial a_0} = -2 \sum_{i=1}^{N} (Y_i - a_0 - a_1 W_i) \\ \dfrac{\partial J}{\partial a_1} = -2 \sum_{i=1}^{N} (Y_i - a_0 - a_1 W_i) \end{cases} \tag{7}$$

given the derivative is equal to 0, the equations can be rewritten as:

$$\begin{cases} \sum_{i=1}^{N} Y_i = a_0 N + a_1 \sum_{i=1}^{N} W_i \\ \sum_{i=1}^{N} W_i Y_i = a_0 \sum_{i=1}^{N} W_i + a_1 \sum_{i=1}^{N} W_i^2 \end{cases} \tag{8}$$

solve these equations can get:

$$\begin{cases} \alpha_1 = \dfrac{\sum_{i=1}^{N}(W_i - \frac{1}{N}\sum_{i=1}^{N} W_i)(Y_i - \frac{1}{N}\sum_{i=1}^{N} Y_i)}{\sum_{i=1}^{N}(W_i - \frac{1}{N}\sum_{i=1}^{N} W_i)^2} \\ a_0 = \frac{1}{N}\sum_{i=1}^{N} Y_i - a_1 \frac{1}{N}\sum_{i=1}^{N} W_i \end{cases} \tag{9}$$

In which the time sequence stable condition is $\tau_1+\tau_2<1$.

2. The predicting algorithm based on combined ARMA and wavelet transform.

Here the specific checking steps. First, take state as S_t of real flow W_t at the wireless sensor network base station *o*. Mainly concerned the delay D_t and column length L_t for reducing the sudden of real flow and improving the predicting accuracy. Analyze the current and past real flow state to gain next flow Z_{t+1} to conduct a reasonable sequence manage. thereafter are the proper predicting algorithm for real flow:

step 1, initial network topology and correlated parameters at the beginning when *t*=0;

step 2, record the state vector S_t of real flow W_t at T when *t*=0, and introduce to ARMA to check if it satisfied the model, if it is then move to step 3, or move to step 7;

step 3, compute the delay D_{t+1} and column length L_{t+1} of real flow of time *t*+1:

$$\begin{cases} D'_{t+1} = 1-(1-\lambda)\sum_{n=0}^{\infty}\Omega_{m+n+1}((n+1)b-t) \\ L'_{t+1} = (1-\lambda)\sum_{n=0}^{\infty}\Omega_{k+n}(n+1)b \end{cases} \tag{10}$$

where λ is size of base burden, *b* is buffer size, and $\Omega k+n$ is distribution function of real flow.

step 4, introduce wavelet transform to process the real flow because of the sudden and length, and then combine the predicted results with what yielded in step 2 to minimize the error. decompose delay D_t and column length L_t of W_t with DB2 wavelets can get scale coefficient $a_j(k)$ and wavelet coefficient $d_j(k)$:

$$\begin{cases} \sqrt{2}a_j(k) = a_{j+1}(2k) + a_{j+1}(2k+1) \\ \sqrt{2}d_j(k) = d_{j+1}(2k) + d_{j+1}(2k+1) \end{cases} \tag{12}$$

step 5, employ ARMA to predict wavelet coefficients. evaluate AR(*p*) parameters $\tau(1)$, $\tau(2)$, ..., $\tau(p)$ and filtering by the FIR filter $A(z) = 1 + \sum_{k=1}^{p}\tau(k)z^{-k}$, an approximation process *MA(q)* can be derived: $\rho(1)$, $\rho(2)$,$\rho(3)$, …, $\rho(q)$, as well parameters *p* and *q*. The predicted wavelet coefficient are also computed through Eq.(6), and then synthesize the delay D''_{t+1} and column length L''_{t+1}:

$$\begin{cases} D''_{t+1} = -\sum_{k=1}^{p}\tau_k D_{t-k} + \sum_{k=0}^{q}\rho_k u_{t-k} \\ L''_{t+1} = -\sum_{k=1}^{p}\tau_k L_{t-k} + \sum_{k=0}^{q}\rho_k u_{t-k} \end{cases} \tag{13}$$

step 6. take the combine operations for less error to the states of delay and column length at time *t*+1 from step 2 and step 4:

$$\begin{cases} D_{t+1} = \phi D'_{t+1} + \varphi D''_{t+1} \\ L_{t+1} = \phi L'_{t+1} + \varphi L''_{t+1} \end{cases} \tag{14}$$

where ϕ and φ are two weighting factors of two different predictions which can be adjusted to gain an optimized result, also define $0 \le \phi \le 1$，$0 \le \varphi \le 1$，$\phi + \varphi = 1$；

step 7, given $t=t+1$ and then move to step one, and then run the compute again till the end.
step 8, runs over.

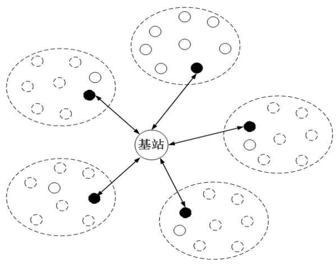

Fig.1 simulation condition

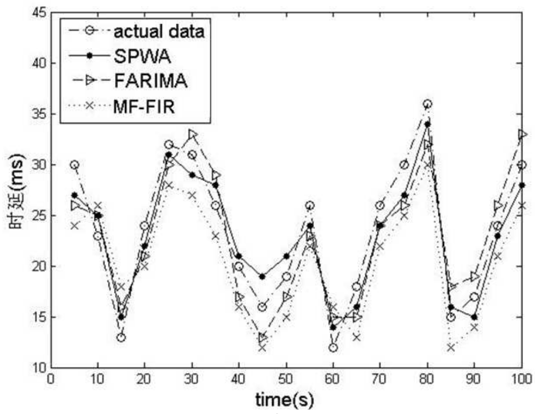

Fig.2 comparison of delay prediction

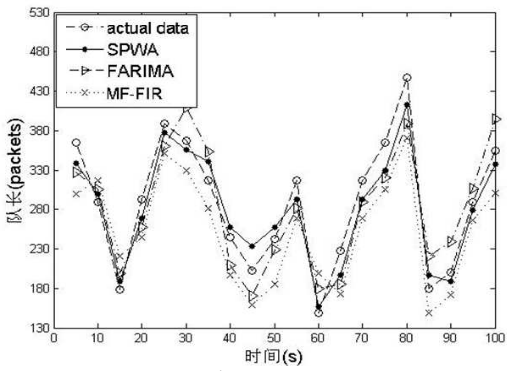

Fig.3 comparison of column length prediction

3. Simulation

Simulations run in OPNET and MATLAB to evaluate the effective of the SPWA. the condition is: Inter Pentium CPU G2020 2.9G, ROM 4G. Start with constructing a wireless network topology: there are totally 30 data knots. Set the link capacity is equal to 15M, delay is 10ms, buffer capacity is 100 packets for normal knots, buffer capacity is 1000 packets for base knots, data package is 128B, and combine parameters $\phi=\varphi=1$, and 12 decomposing layers for the wavelet transform. To show the accuracy of SPWA, by comparing with FARIMA model[16] and MF-FIR model [17]described by fractal and to show the predicting accuracy, each of those two models run 30 times simulation and then take the average, show delays column lengths in Fig. 2 and Fig. 3. It is clearly that the SPWA has a better prediction result while FARIMA model bring bigger error. one can find that FARIMA has a larger amount of computing which leads delay in dynamic transformation in real flow. One can figure out that errors by SPWA、FAEIMA and MF-FIR are 15.34%、 21.57% and 25.34% respectively.

This paper also studied algorithm, especially the effects over variation of key parameters. here taking real flow X and its coefficient function $X \sim S_{\alpha}(\sigma, \beta, \mu)$, see

$$\Phi(\omega) = E[e^{j\omega X}] = \begin{cases} \exp\{ j\mu\omega - |\sigma\omega|^{\alpha} [1 - j\beta \operatorname{sgn}(\omega) \tan(\frac{\pi\alpha}{2})]\}, \alpha \neq 1 \\ \exp\{ j\mu\omega - |\sigma\omega|^{\alpha} [1 + j\beta \operatorname{sgn}(\omega) \frac{2}{\pi} \ln|\omega|]\}, \alpha = 1 \end{cases} \quad (15)$$

where α(0< α<2) is characteristic parameter which is used to present burst degree and fractal state of real flow, β (-1< β <1) is deviation scale parameter, density function shape of real flow is determined by α and β. σ (σ≥0) is deviation scale parameter which represents deviation of distribution, while μ is location parameter which is used to represent average quantity. One can read from Fig. 4 and Fig. 5 that the delay prediction error has a tendency of at first decrease and then increase. When δ is small, bigger α means smaller delay prediction error, while larger delay prediction error when α is growing. This is because bigger α represents bigger real flow. In this paper, ARMA model and wavelet transform are combined for predicting, small δ means wavelet play weights more than ARMA(δ+η=1), wavelet transform is good at erasing emergencies so it shows less prediction error when α is less. When δ is bigger, α play a more important role in low emergency, that's why smaller α leads smaller prediction error. Also one can read this phenomenon in Fig.4, when δ is small, bigger α leads to small prediction error, and wen δ is bigger enough, the error hopping contrarily.

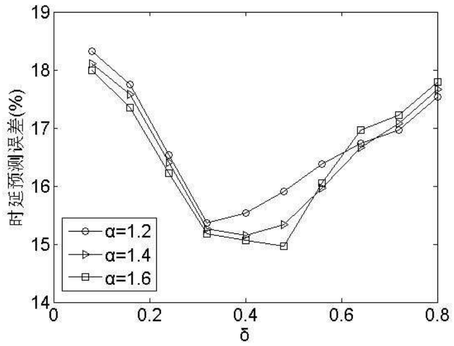

Fig. 5 delay prediction error over *δ*.

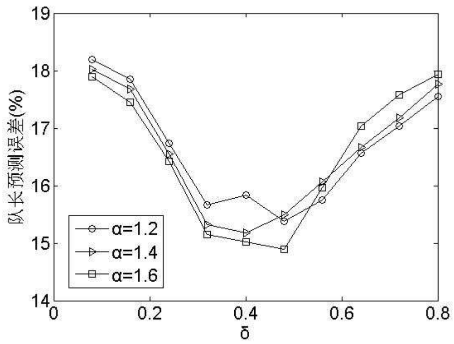

Fig. 5 Column length prediction error over *δ*.

CONCLUSION

In this paper, a new prediction algorithm is proposed based on ARMA and wavelet transform for wireless network real flow prediction accuracy. After defining ARMA model, and then constructing the new predicting methods based on a combined ARMA and wavelet transform to reduce the prediction error, at last, run a series of simulation to study the key factors in this new algorithm. After comparing with FARIMA model and MF-FIR model, SPWA has better applicability.

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