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Signal Detection Based on Particle Swarm Optimization for MIMO-OFDM System

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Abstract

In order to overcome the defects of the slow convergence rate of the traditional Genetic Algorithm and basic Particle Swarm Optimization drops into local optimum easily, an improved Particle Swarm Optimization algorithm based on hybrid algorithm is proposed and applied to the signal detection for MIMO-OFDM system. The algorithm optimizes the basic Particle Swarm Optimization algorithm and some problems were solved by means of Particle Swarm Optimization combined with Genetic Algorithm for signal detection. Through the theoretical analysis and the simulation research, this improved algorithm is superior to basic Particle Swarm Optimization algorithm 0.5dB under the same number of iterations and is better than traditional Genetic Algorithm 0.5dB under the same bit error rate. This algorithm improves the system signal detection performance effectively with less iteration and reduces the bit error rate. It has rapid speed of convergence and strong capability of global search.

Keywords: *MIMO, OFDM, particle swarm optimization, hybrid algorithm, signal detection*

1. Introduction

The combination of Orthogonal Frequency Division Multiplexing (OFDM) and Multiple Input Multiple Output (MIMO) is one of key technologies in the fourth generation of mobile telecommunication [1]. OFDM can improve the spectral efficiency and spatial multiplexing gain of a system can be extracted through MIMO technique. In this way, the combination of them can improve the spectral efficiency and data transmission rates. Meanwhile, introducing MIMO to OFDM can achieve broadband OFDM system, which is adopting transmitter array which consists of a large number of low-power transmitters to eliminate the shadow effect and achieve full coverage. MIMO system can combat multi-path fading, but it is not suitable for frequency selective fading channel in the MIMO system, which can be overcome by OFDM [2]. The Guard Interval (GI) can eliminate inter-symbol interference (ISI) and Cyclic Prefix (CP) can eliminate Inter-carrier Interference (ICI).

In order to achieve excellent transmission performance for MIMO-OFDM system, precise signal detection is very necessary before demodulation [3]. In MIMO-OFDM system, the performance and the complexity of signal detection algorithm of system receiver will directly affect the quality of the entire communication system. Signal detection algorithm with excellent detection performance is often accompanied by higher complexity; the realization of high complexity algorithm is often limited by hardware processing capability. Therefore, developing an algorithm with optimal signal detection performance and moderate complexity is the key to achieve satisfactory performance of receiver for MIMO-OFDM system. Signal detection methods generally include linear detection and nonlinear detection in the field of signal detection for MIMO-OFDM system so far. The research of linear detection mainly focuses on Zero Forcing (ZF) detection [4], Minimum Mean Square Error (MMSE) detection [5], and Linear Minimum Mean Square Error (LMMSE) detection [6]. The design of linear detection algorithm is simple and easy to be implemented, but the detection performance is worse, it is not suitable to be applied separately in practical system. The research in nonlinear detection mainly focuses on QR decomposition detection algorithm [7], Serial Interference Cancellation detection algorithm [8] and V-BLAST detection algorithm [9].The above algorithms detect layer by layer to eliminate

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the interference, their performance is limited by the first linear detection accuracy. The error of the first linear detection results will increase the error probability of interference cancellation in the second detection and bring cumulative error.

Many intelligent optimization algorithms have been put forward, these kinds of detection algorithms are proposed based on the local optimization of intelligence algorithm. Intelligent algorithm can solve the optimization problem of functions, such as calculating the maximum value or the minimum value of a function in a solution space .In the field of signal detection, intelligent algorithm takes the maximum likelihood function as the objective function and all possible transmit signal vector as the solution space. The algorithm imitates the natural processes of intelligent optimization in colonial organisms to find the optimal transmit signal. These signal detection methods first appeared in the CDMA system multi-user detection. Kechriotis applied Hopfield neural network to the CDMA system to solve the maximum likelihood detection which is a NP problem [10]. Jiang Ming and Hanzo proposed a multi-user detection algorithm based on Genetic Algorithm for MIMO-OFDM systems [11]. Louw and Botha proposed sphere detection based on Hopfield neural network for MIMO system [12]. Higuchi and Kaiwa proposed a MIMO system signal detection algorithm based on taboo search [13].

In this paper, we present an improved Particle Swarm Optimization signal detection algorithm with good performance and lower complexity with the same number of iterations and bit error rate, which is combining hybrid genetic algorithm with basic Particle Swarm Optimization to minimize the negative effects of the error diffusion, its performance is superior to other traditional algorithms. The rest of the paper is organized as follows. Firstly, we describe the system model of MIMO-OFDM. Secondly, the proposed signal detector of MIMO-OFDM system based on Particle Swarm Optimization signal detection algorithm is introduce, and the simulation results are obtained. Finally, some conclusions are drawn in this section.

2. System Model

The system block diagram of MIMO-OFDM is shown as Figure 1. The transmitted signals go through code mapping. before passing the serial-to-parallel conversion and IFFT modulation. At last, a cyclic prefix is added to them. They are transmitted via different transmit antenna respectively. After going through a frequency-selective channel, the receivers firstly move the cyclic prefix from the signals. Secondly, the received signals are transformed by FFT ,and then pass through a parallel-to-serial conversion. Finally, the received signals go through a decoder and the receivers get the recovered original data.

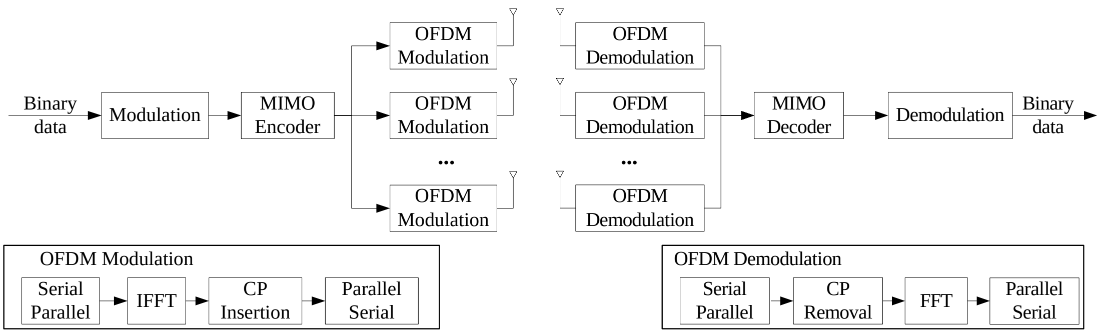

Figure 1. Block Diagram of a MIMO-OFDM System Model

For a MIMO system with Nt transmitting antennas and Nr receiving antennas, high-speed data streams go through a serial-to-parallel conversion, there is N_d data in each group. The vector form of the n-th set of data in the i_t-th transmitting antenna is as follows:

$$d_{i_t}(n) = \left[d_{i_t}(0,n), d_{i_t}(1,n), \cdots, d_{i_t}(N_d - 1, n)\right]^T \quad (1)$$

In order to eliminate the effects of ISI and ICI, d_{i_t} is coupled with a Cyclic Prefix whose length is N_{CP} after the IFFT transformation, then we can get the time-domain OFDM symbol. The vector form of the n-th OFDM symbol in the i_t-th transmitting antenna is as follows:

$$x_{i_t}(n) = \left[x_{i_t}(0,n), x_{i_t}(1,n), \cdots x_{i_t}(N_d + N_{CP} - 1, n)\right]^T \quad (2)$$

Where,

$$x_{i_t}(m,n) = \sum_{i=0}^{N_d-1} d_{i_t}(l,n) \exp\left(j2\pi l \frac{m - N_{CP}}{N_d} \right) \quad (3)$$

The receiving antenna remove the cyclic prefix from the received signals then carry out the FFT transform and get the initial data of the transmitter in frequency domain. The n-th OFDM signal at the k-th subcarrier received by the i_r-th receiving antenna can be described as:

$$Y_{i_r}(k,n) = \sum_{i_t=0}^{N_t-1} H_{i_r,i_t}(k) X_{i_t}(k,n) + W_{i_r}(k,n) \quad (4)$$

Then, we can get the matrix form of the MIMO-OFDM transmission system model as:

$$Y(k,n) = H(k) X(k,n) + W(k,n) \quad (5)$$

Where, $Y(k,n) = [Y_0(k,n), Y_1(k,n), \cdots, Y_{Nr-1}(k,n)]^T$ represents received signal vector at the k-th subcarrier; $X(k,n) = [X_0(k,n), X_1(k,n), \cdots, X_{Nt-1}(k,n)]^T$ represents transmitted signal vector at the k-th subcarrier; $W(k,n) = [W_0(k,n), W_1(k,n), \cdots, W_{Nr-1}(k,n)]^T$ represents the noise vector. $H(k)$ means the channel frequency response matrix of the k-th subcarrier, it can be described as follows:

$$H(k) = \begin{bmatrix} H_{0,0}(k) & H_{1,0}(k) & \cdots & H_{Nt-1,0}(k) \\ H_{0,1}(k) & H_{1,1}(k) & \cdots & H_{Nt-1,1}(k) \\ \vdots & \vdots & \ddots & \vdots \\ H_{0,Nr-1}(k) & H_{1,Nr-1}(k) & \cdots & H_{Nt-1,Nr-1}(k) \end{bmatrix} \quad (6)$$

3. Detection Process and Optimiztion Algorithm Description

3.1. Particle Swarm Optimization Algorithm

In1995, Dr. Eberhart and Dr. Kennedy proposed Particle Swarm Optimization algorithm [15]. It is an evolutionary technology, originating from the research on bird flock preying behavior. Particle swarm Optimization is based on the observation of cluster activity behavior, it uses the information sharing of individuals in group to make the entire group move from disorder to order in the solving space and finally obtain the optimal solution. All the particles have a fitness value determined by the optimization function and a speed determines the direction and distance. The particles adjust the speed dynamically according to its own flying experience as well as the flying experience from their companion.

The initialization is a group of random particles. Then we can get the optimal solution through iteration. During each iteration, the particles update themselves by tracking two extremes. The first is the optimal solution found by the particle itself. This solution is called personal best. The other extreme is called group best, which is the optimal solution of the entire group. Assume that there is a community composed of N particles in a D-dimensional search space, each particles represents as a D-dimensional vector.

$$X_i = (x_{i1}, x_{i2}, \cdots, x_{iD}), i = 1,2,\cdots,N \tag{7}$$

The speed of the particle is a D-dimensional vector, denoted as

$$V_\mathrm{i} = (v_{i1}, v_{i2}, \cdots, v_{iD}), i = 1,2,\cdots,N \tag{8}$$

Personal best is also a D-dimensional vector, denoted as

$$p_{best} = (p_{i1}, p_{i2}, \cdots, p_{iD}), i = 1,2,\cdots,N \tag{9}$$

When finding the two best values, the particles update the speed and position according to the following Equation (10) and (11).

$$v_{id}^{q+1} = wv_{id}^{q} + c_1 r_1 \left(p_{id}^{q} - x_{id}^{q}\right) + c_2 r_2 (p_{gd}^{q} - x_{id}^{q}) \tag{10}$$

$$x_{id}^{q+1} = x_{id}^{q} + v_{id}^{q+1} \tag{11}$$

3.2. Signal Detection Process Based on Particle Swarm Optimization Algorithm

A signal detection scheme based on Particle Swarm Optimization algorithm for MIMO-OFDM system is designed in this paper. In order to achieve a sufficiently good performance of Particle Swarm Optimization signal detection algorithm, the main parameters of Particle Swarm Optimization algorithm are designed as follows:

Firstly, species initialization. q is the number of iterations; c_1, c_2 is the acceleration coefficient, they usually equal 2; $r_{1,2}$ is a random number between 0 to 1; v_{id}^{q} is the speed in dth-dimension of the qth iteration of particle i; x_{id} is the current position of particle i in dth-dimension; p_{id} is the best position of particle i in dth-dimension; p_{gd} is the best position of whole group in d th-dimension.

Secondly, parameter settings. In order to prevent the particles away from the search space, the particle velocity of each dimension will be confined to $[-v_{d\max}, +v_{d\max}]$, generally $v_{d\max} = kx_{d\max}, 0.1 \le k \le 1$, each dimension use the same settings.

Finally, the selection of the fitness function. The fitness function is the standard based on the maximum likelihood to assessment the system detection performance good or bad, and it is non-negative:

$$\hat{\chi} = \arg\min_{x\in\phi} \{\|y - H \bullet X\|^2\} = \arg\max_{x\in\phi} [2x^T H^T y - x^T H^T Hx] \tag{12}$$

Set the objective function of the MIMO-OFDM signal detector as:

$$\Omega(x) = 2x^T H^T y - x^T H^T Hx \tag{13}$$

Assume that the objective function achieves maximum value when x is b, then the objective function value is $\Omega(b)$, because $\Omega(b)$ can be positive or negative, in order to ensure the fitness function is non-negative, the fitness function in signal detection is set as:

$$f(b) = \exp(\mu \bullet \Omega(b)) \quad (14)$$

Where μ is a normal number in the experiment of this paper, μ is set to 0.1. So that the best detection of the MIMO-OFDM signal can be described as a PSO optimal individual, that is the output of the detection.

3.3. MIMO-OFDM Signal Detection Process Based on improved Particle Swarm Optimization

In order to overcome the problem of basic Particle Swarm Optimization algorithm easily fall into local extremum, it is required to find an algorithm with good global search ability, the Genetic Algorithm can effectively prevent the search process falling into local extremum [16]. This algorithm is based on the principle of hybrid in Genetic algorithm. In each iteration, a specified number of particles are selected into the hybrid pool according to hybridization probability. Particles hybridize randomly in the pool and then produce the same number of filial generation particles. After that, filial generation particles substitute the parental particles. The position of filial generation is calculated by the arithmetic crossover of the parental position:

$$x_{child}^{q+1} = p \cdot x_{parent_1}^{q} + (1-p) \cdot x_{parent_2}^{q} \quad (15)$$

Where p is a random number between 0 to 1. The speed of filial generation is calculated by (16).

$$v_{child}^{q+1} = \frac{v_{parent_1}^{q} + v_{parent_2}^{q}}{\left|v_{parent_1}^{q} + v_{parent_2}^{q}\right|} \cdot \left|v_{parent_1}^{q}\right| \quad (16)$$

The detection steps based on hybrid particle swarm algorithm optimization are as follows:

Step 1: Initialize the position x and speed v of each particle randomly.

Step 2: Evaluate the fitness of each particle and store the current position and the adaptation values in the best position of each particle, then store the best individual fitness value among all pbest in the gbest.

Step 3: Update the speed v and position x of each particle.

Step 4: Compare the fitness value of each particle as shown in (14) with the best position it has experienced and take the better one as the current best position;

Step 5: Compare the current value of p_{id} and p_{gd} then update the gbest.

Step 6: Elect a specified number of particles into the hybrid pool according to hybridization probability, particles hybridized randomly in the pool and produce the same number of filial generation particles (child), then update the position and velocity of the filial generation by (15) and (16), maintaining p_{id} and p_{gd} unchanged.

Step 7: Stop when condition which is the computing precision or the number of iterations is met, the search stops and outputs results, otherwise returns to step3 to continue the search.

When the preset number of iterations and accuracy is reached, the search stops and the output result is the optimal detection signal.

4. Simulation Results

In this paper, the simulation of the algorithms mentioned before is conducted to demonstrate the performance of the proposed signal detection method. The simulation parameter values are shown in Table 1. Assuming that the sending and receiving antennas are independent. The simulations are performed in a 4×4 MIMO-OFDM system with one path. We assume that the channel state information (CSI) is known. The sender uses the modulation of BPSK and 8QAM. The transmission power of the sender is 1. Each noise is complex-valued additive Gaussian white noise, and it is independent and identically distributed Gaussian white noise with zero mean; the MIMO-OFDM system is single path.

Table 1. Table of Parameters Setting for Algorithm Simulation

Parameter	value
Maximum velocity	3.5
Inertia weight	[0.4,0.9]
Acceleration coefficient(c1)	2
Acceleration coefficient(c2)	2
Length of CP	512
Points of FFT	2048
Transmitting antenna	4
Receiving antenna	4

Figure 2 shows the difference in the bit error rate under the condition of different iterations and simulation parameters between improved particle swarm optimization detection algorithm and maximum likelihood detection algorithm.

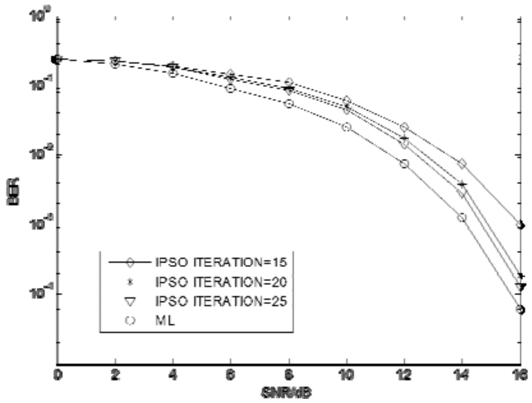

Figure 2. BER of IPSO Algorithm in Different Iterations

The simulation results show that the maximum number of iterations of 25 is superior to the maximum number of iterations is 20 and 15 under the improved Particle Swarm Optimization algorithm. The maximum number of iterations 20 is better than the maximum number of iterations 15 with about 0.5dB, but there is no significant increase in performance of maximum number of iterations 25 to 20. The reason is gain reduction due to the error accumulation with the increase of the number of iterations. At the same time, its performance is closer to optimal ML (Maximum Likelihood) detector when the maximum number of iterations is 20, but has lower computing cost. We can conclude that the proposed algorithm can detect signal well and has faster convergence speed.

Figure 3 and Figure 4 give the bit error rate performance curve of the Maximum Likelihood detection algorithm, Zero-Forcing detection algorithm, Particle Swarm Optimization detection algorithm, Genetic Algorithm detection and improved Particle Swarm Optimization detection algorithm based on hybrid under the same simulation parameters in the modulation scheme of BPSK and 8QAM respectively.

The simulation results show that: Both in BPSK and 8QAM modulation mode, the performance of the improved Particle Swarm Optimization based on hybrid is significantly improved compared with Zero Forcing detection algorithm, Particle Swarm detection algorithm and Genetic Algorithm with the same number of iteration. This is because that the improved Particle Swarm Optimization algorithm has stronger global search ability and faster convergence rate. In the case of the same maximum iteration time of 20, there is only 0.5dB difference between its performance and Maximum Likelihood algorithm, but it has lower compute complexity.

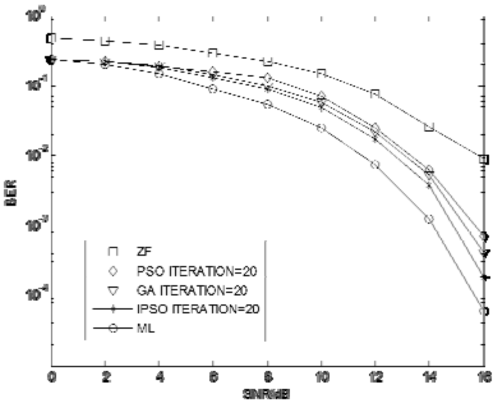

Figure 3. BER of Different Detection Algorithms under BPSK

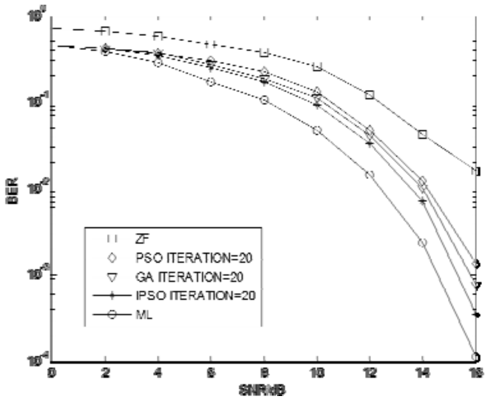

Figure 4. BER of Different Detection Algorithms under 8QAM

5. Conclusion

In this paper, we propose an improved Particle Swarm Optimization algorithm which combines Genetic Algorithm and Particle Swarm Optimization algorithm to detect signals for MIMO-OFDM system. We assume that the channel information is accurate. It is a comprehensive utilization of the good global convergence of Genetic Algorithm and the quick learning ability of Particle Swarm Optimization algorithm, so that the hybrid optimization algorithm has better parallel processing power and faster convergence than the traditional algorithms. We simulate and analyze the algorithms mentioned in this paper and compare the performances between different algorithms. Simulation results show that the improved Particle Swarm Optimization algorithm is better than traditional Genetic Algorithm and Particle Swarm Optimization algorithm, its performance is close to the ideal detection of Maximum Likelihood algorithm. Signal-to-noise ratio loss is only 0.5 dB. Besides, the complexity is relatively low. The results demonstrate the effectiveness and the applicability of improved Particle Swarm Optimization in signal detection for MIMO-OFDM systems.

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References

[1] Du Yuelin, Zhang Jingxian. The performance of synchronization algorithm in real-time OFDM-PON system. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(7): 1784-1794.
[2] Zhu Yonghong, Feng Qing, Wang Jianhong. Neural network-based adaptive passive output feedback control for MIMO uncertain system. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 10(6): 1263-1272.
[3] JingPeng Gao, DanFeng Zhao, ChaoQun Wu. A Joint Synchronization and Channel Estimation Algorithm for MIMO-OFDM System. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2013; 11(12): 7571-7579.
[4] Wan F, Zhu WP, Swamy MNS. Channel estimation of pulse-shaped multiple-input multiple-output orthogonal frequency division multiplexing systems. *IET Communications*. 2010; 4(17): 2104-2114.
[5] Siriteanu C, Miyanaga Y, Blostein S D,et al. MIMO Zero-Forcing Detection Analysis for Correlated and Estimated Rician Fading. *IEEE Transactions on Vehicular Technology*. 2012; 61(7): 3087-3099.
[6] Chisaguano DJR, Okada M. *ESPAR antenna assisted MIMO-OFDM receiver using sub-matrix divided MMSE sparse-SQRD detection*. 2012 International Symposium on Communications and Information Technologies (ISCIT). QLD. 2012: 198-203.

[7] Xiaojun Yuan, Li Ping. *Space-time linear precoding and iterative LMMSE detection for MIMO channels without CSIT*. 2011 IEEE International Symposium on Information Theory Proceedings (ISIT). Petersburg. 2011: 1297-1301.
[8] Kuanghao Lin, Chang RC, Chienlin Huang, et al. *Implementation of QR decomposition for MIMO-OFDM detection systems*. 15th IEEE International Conference on Electronics, Circuits and Systems (ICECS). Julien. 2008: 57-60.
[9] Buzzi S, Saturnino D. SINR-maximizing spreading code allocation for non-linear serial interference cancellation. *IEEE Transactions on Communications*. 2010; 58(2): 631-641.
[10] Lee K, Joohwan Chun. Symbol detection in V-BLAST architectures under channel estimation errors. *IEEE Transactions on Wireless Communications*. 2007; 6(2): 593-597.
[11] Weixin Gao, Nan Tang, Xiangyang Mu. *An Algorithm for Unit Commitment Based on Hopfield Neural Network*. Fourth International Conference on Natural Computation (ICNC). Jinan. 2008; 2: 286-290.
[12] Jiang M, Akhtman J, Hanzo L. Iterative Joint Channel Estimation and Multi-User Detection for Multiple-Antenna Aided OFDM Systems. *IEEE Transactions on Wireless Communications*. 2007; 6(8): 2904-2914.
[13] Radosavljevic P, Yuanbin Guo, Cavallaro J. Probabilistically bounded soft sphere detection for MIMO-OFDM receivers: algorithm and system architecture. *IEEE Journal on Selected Areas in Communications*. 2009; 27(8): 1318-1330.
[14] Taspinar N, Kalinli A, Yildirim M. Partial Transmit Sequences for PAPR Reduction Using Parallel Tabu Search Algorithm in OFDM Systems. *IEEE Communications Letters*. 2011; 15(9): 974-976.
[15] Hsuehhsien Chang, Lungshu Lin, Nanming Chen,et al. Particle-Swarm-Optimization-Based Nonintrusive Demand Monitoring and Load Identification in Smart Meters. *IEEE Transactions on Industry Applications*. 2013; 49(5): 2229-2236.
[16] Fei Li, Wei Wang. *Quantum genetic algorithm based signal detection scheme for MIMO-OFDM system*. International Conference on Communication Systems, Networks and Applications (ICCSNA). Hong Kong. 2010; 1: 298-301.