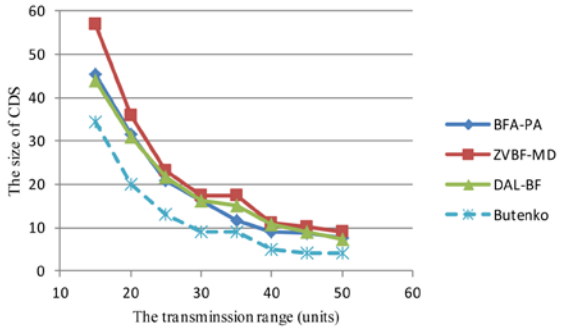

Fig.8. The size of CDS when Tr is changed and SN equals 200.

Message overhead is another metric of the CDS formation algorithm. In the wireless sensor network, the hosts suffer from strict resource limitations so that the communication overhead should be kept as low as possible. Fig.9 and Fig. 10 show the message overhead of different algorithms when the size of the network is changedand Tr is set to15 and 30, respectively.The message overhead of DAL-BF is not shown in the figures because its message overhead is large. For example, when SN is 100 and Tr is 15 units, the message overhead DAL-BF is more than 400 thousands bytes. Based on those results, we can find that BFA-PA has alarge message overhead than ZVBF-MD. This is cause by the fact that, in BFA-PA, each dominator will get its action set and send the set to the sink. On the other hand, in ZVBF-MD, only the dominator at the zone border executes a similar process. We also could find that the number of message overhead increases when the number of nodes or Tr increases.

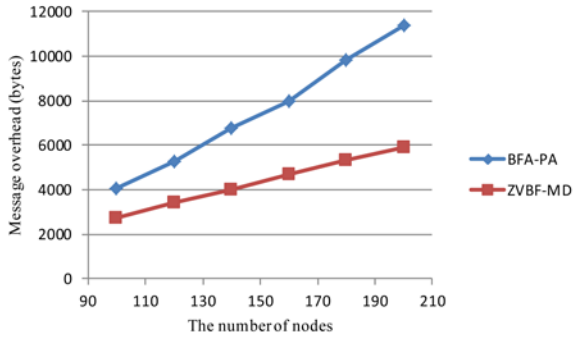

Fig.9. The Average messageoverhead when SN is changed and Tr equals15 units.

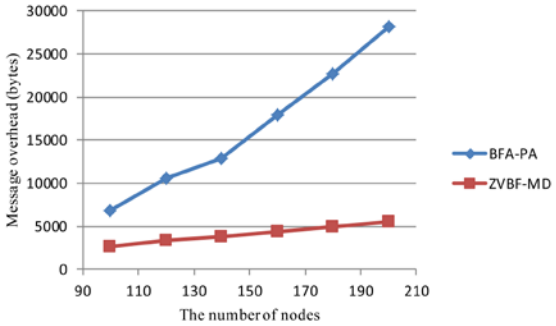

Fig.10. The Average messageoverhead when SN is changed and Tr equals 30 units.

The average node degree in the CDS is another parameter proposed by Bo [3], which is also the average node degree in the induced sub graph of the constructed CDS. Bo believes that a low degree may cause less interference for communication. Both Fig. 11 and Fig. 12 show the experiment results when the value of SN changes from 100 to 500, and Tris set as 15 and 30 units, respectively. Based on those results, we can get that the node degree in the CDS increases when the size of network increases and Trincreases. When the network is dense (T*r* is set as 30 units and SN is more than 300), the rising trends of those algorithms are not conspicuous any more, and BVF-PA has similar performance to ZVBF-MD.

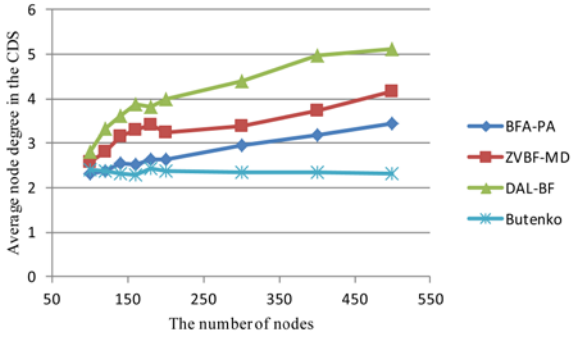

Fig.11.Average node degree in the CDS when SN is changed and *Tr* equals 15 units.

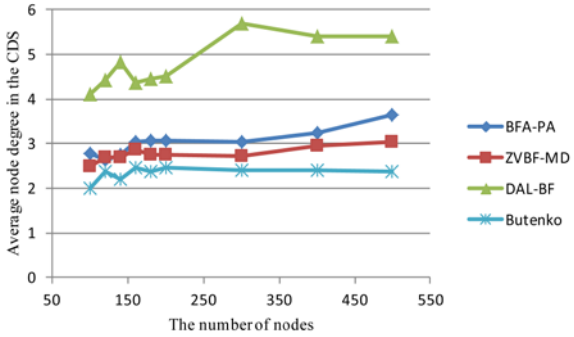

Fig.12. Average node degree in the CDS when SN is changed and *Tr* equals 30 units.

7 Conclusion

In this paper, based on the pursuit algorithm, we propose a novel backbone formation algorithm, called BFA-PA. In this algorithm, a DS is got at first and each node in the DS gets its action set based on the connection path between the dominator and their 2 or 3 hops dominator neighbors. Sink executes the pursuit algorithm and treads dominators as automata with to get an approximate solution of MCDS of network. Moreover, a changing speed of learning parameter is used to avoid choosing a special learning rate, which should be carefully selected to make a trade-off between the convergence speed and the size of backbone. It is also shown that our method is ε-optimality to connect the DS with the changing speed of learning parameter. According to the results of the simulation, our algorithm generates a smaller CDS than ZVBF-MD and has a similar result with DLA-BF about the size of CDS. However, it is efficient than DLA-BF because it has a small overhead.

However, in this algorithm, we assume that the network is stationary. When some new sensor nodes are added to the network or removed, the algorithm should be run again to get a backbone of network. Because the topology of network is changed, BFA-PA is difficult to work on a dynamic network. Is there a simple method to fix the backbone when there are some additions or failures of nodes? The answer to this question is significant to the further application of this method, and it will be a guide for our future work.

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