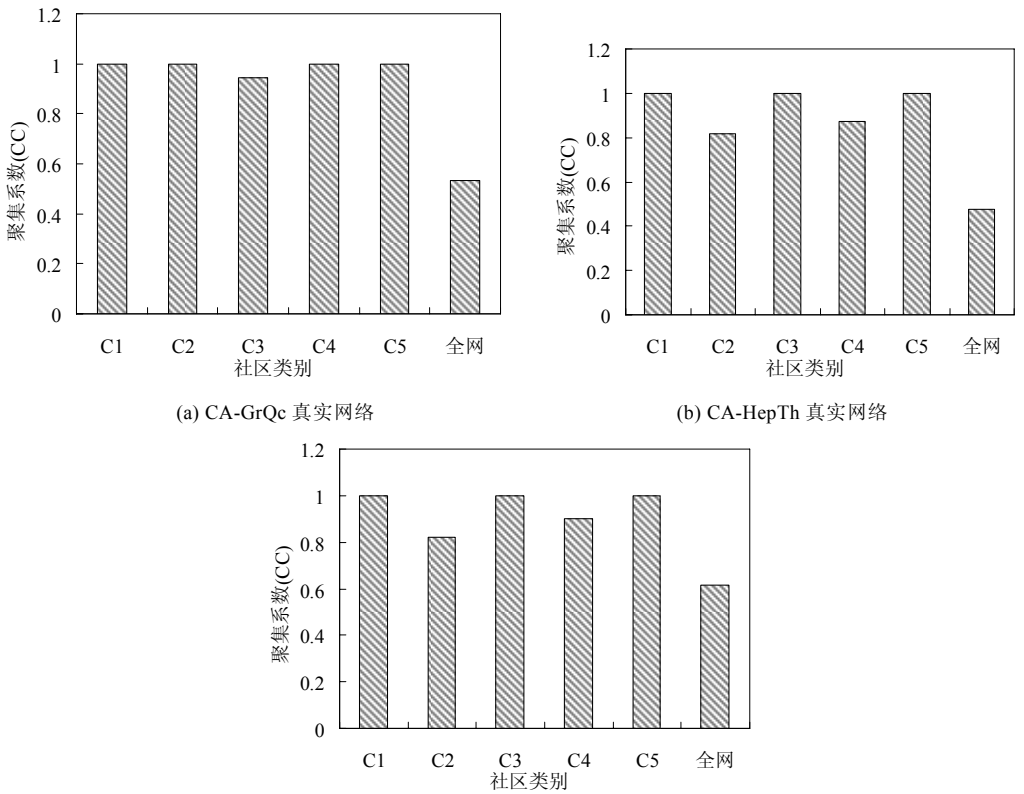
$$\bar{C}=\frac{1}{n}\sum_{i=1}^{n}C_i \tag{15}$$

若一个社区内所有节点的平均 *CC* 远大于整个网络作为一个社区时所有节点的平均 *CC*,说明所识别出的社区结构是有意义的,进而说明了社区识别质量很高.

以图 7(a)为例进行说明,图 7(b)、图 7(c)的情况类似.图 7(a)显示了 CA-GrQc 随机选取社区的聚集系数及全网聚集系数对比,其中:社区 *C*1,*C*2,*C*4,*C*5 的聚集系数达到 1,说明这一社区内部任意一个节点的邻接节点互相之间均有边相联系;*C*3 社区的聚集系数也达到了极高的 0.944 4.同时,全网的聚集系数为 0.532 0.说明网络的社区特征并不是很明显的情况下,算法仍能较准确地识别网络的社区结构,具有较高的识别质量.



(a) CA-GrQc 真实网络

(b) CA-HepTh 真实网络

(c) CA-HepPh 真实网络

Fig.7 Clustering coefficient of DOC algorithm under SNAP real networks

图 7 DOC 算法在 SNAP 真实网络大数据下社区聚集系数

4.4 算法运行时间性能分析

本节将通过对比不同算法在 LFR 基准数据集上的实验效果来验证本文所提算法的时间性能优势.

图 8 表示在 LFR 基准数据集(数据集 *A*)上 DOC 算法的运行时间近似线性变化,与本文第 3.4 节所提的时间复杂度 $O(n\log^2(n))$吻合,明显优于传统算法的时间复杂度.其他数据集上的实验结果类似,这里不再赘述.图 8 说明,DOC 相比于 COPRA 和 SLPA 算法在时间性能上有极大的提高.原因在于:DOC 算法通过建立平衡二叉树、对模块度增量建立索引,使得每次算法寻找最大的模块度增量的复杂程度降低.因为 CONGA 算法时间复杂度较高,为 $O(m^2n)$,最坏情况为 $O(m^3)$,算法运行时间性能较差,本节实验没有给出算法运行时间.

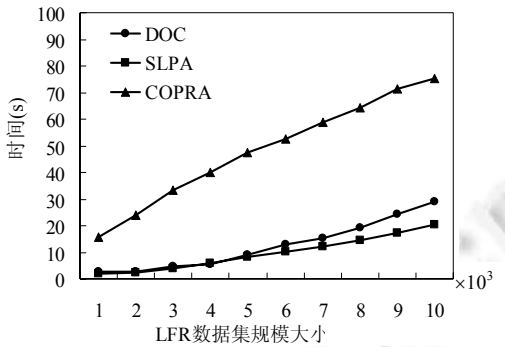


Fig.8 Runtime comparison of different algorithms under LFR benchmark network dataset *A*

图 8 不同算法在 LFR 基准数据集 *A* 上运行时间对比

5 结束语

本文提出了针对复杂网络大数据的重叠社区检测算法,算法基于模块度和图计算的思想,采用了新的节点和边的更新方法,利用平衡二叉树优化经典无重叠社区发现 Fast-Newman 算法,提高了节点更新的效率.进行大量实验结果后的表明:本文所提出的算法能够准确地检测重叠社区节点,同时极大地降低了算法的时间复杂度.

未来工作包括:将算法应用于为真实世界的各类复杂网络大数据中,提供社区识别服务,进而给用户提供包括兴趣点推荐等多种个性化服务.因为由于网络用户信息的不断更新,设计新算法实现社区的实时检测.此外,将在静态社区检测基础上设计动态网络社区检测算法,提高社区检测算法在实际网络中的应用价值.

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