Decentralized Distributed Bayesian Estimation

[1]Dedecius Kamil , [2]Sečkárová Vladimíra

The increasing spatial complexity of modern adaptive wireless and sensor networks and the diversity of its elements call for reliable estimation of several variables of interest. In most regular cases it can be naturally assumed that each participating element carries (to some degree) valid information about these variables and that they could potentially benefit from cooperation and information sharing. We will refer to this *modus operandi* as the distributed estimation [1].

The problem has attained certain attention during past few decades, resulting in several methods, e.g. [2, 3, 4, 5, 6]. The popular and widely used centralized distributed estimation, in which the network nodes communicate their measurements with a single specialized point suffers from high communication overheads and represents a potentially dangerous concept with a single point of failure needing special treatment [5]. The presented distributed estimation method is its decentralized counterpart. Its philosophy is motivated by saving as much resources (time, energy, communication resources. . .) as possible without significantly decreasing the estimation quality.

The basic setting of the decentralized estimation method put the following limitation on the internodal communication: it divides the network into smaller overlapping units (called closed neighbourhoods, Fig. 4) consisting of a node and its adjacent neighbours. This node is allowed to exchange data (measurements, regressors. . .) only within its closed neighbourhood. The Bayesian formulation of the problem and

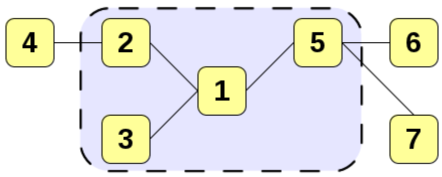

Figure 4: Example of a closed neighbourhood of node 1.

its solution abstracts from any particular model case. This leads to a very scalable and universal method, applicable to a wide class of different models. A particularly interesting case – the Gaussian regressive model – is derived as an example. It coincides with the diffusion recursive least-squares algorithm [5], which proves the method feasibility.

References

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[1]ÚTIA AV ČR, Department of Adaptive Systems, *dedecius@utia.cas.cz*
[2]ÚTIA AV ČR, Department of Adaptive Systems, *seckarov@utia.cas.cz*