Towards Smart Wireless Body-Centric Networks

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Abstract—We investigate the existence of ‘long-memory’ or long-range dependence (LRD) of the wireless body-centric channels, e.g., on-body, body-to-body (B2B), with real-life experimental dataset collected from 10 co-located wireless body area networks or BANs (people fitted with wearable sensors). We examine two different factors on that purpose such as: the pattern of the decaying autocorrelation function (ACF) and the Hurst exponent. From the experimental outcome, we show that, the ACF decay of the body-centric channels follows a power-like decay and the channels have a Hurst exponent much greater than 0.5 on average. These results indicate that the body-centric channels can possess long-memory or LRD characteristic which can be used for predictive analysis and intelligent decision making to build futuristic wireless human-centered networks that can sense and act autonomously. We also clarify whether the presence of the LRD property is sufficient for reliable prediction of the body-centric channels.

I. INTRODUCTION

Wireless body-centric communications are attracting a lot of attention due to the low-cost, suitable new technology for establishing human-to-human or body-to-body networks (BBNs) through wearable sensors. BBNs are envisioned to be self-organizing, smart, and mobile networks that can create their own centralized/decentralized network connection without any external coordination for serving different medical and non-medical applications [1]. This type of autonomous decision making activity requires systematic prediction and modeling of the channel behavior which further depends on the ‘long-memory’ characteristic of the channel. Here, we aim to address the following issues:

• What is ‘long-memory’ and why is it important?
• Do wireless body-centric channels have long-memory?
• Is having long-memory sufficient for making reliable prediction?

II. EXPERIMENTAL SCENARIO

We use an open-access dataset which consists of contiguous extensive intra-BAN (on-body) and inter-BAN (body-to-body) channel gain data of around 45 minutes, captured from 10 closely located mobile subjects (adult male and female) with a sampling rate of 20 Hz. Each subject wore 1 transmitter (Tx hub) on the left-hip and 2 receivers (sensors/ relays) on the left-wrist and right-upper-arm, respectively (Fig. 1). A description of these wearable radios can be found in [2] and the “open-access” dataset can be downloaded from [3].

III. LONG-MEMORY OR LONG-RANGE DEPENDENCE

Long-memory or Long-range dependence (LRD) is the level of statistical dependence between two points in the time series.

The ‘memory’ refers to how strongly the past can influence the future or, how useful is the past data to predict the future consequences. If a channel possesses long-range-dependence then it is more predictable as more data can be used to predict the future.

A. Decaying ACF

A rough analysis of the dependence is to examine the pattern of the decaying autocorrelation function (ACF) of the channel. For a short-memory process, the dependence between two points decreases rapidly with the increase in time difference, hence the ACF has an exponential decay (faster decay) or drops to 0 after a certain time lag. On the other hand, if the channel possesses long-memory the ACF decays more slowly (power-like) than an exponential decay.

We analyze the average ACF of different BAN/BBN channels where we fit the single term exponential and power series models to the ACF decay in MATLAB, which uses the trust-region algorithm with nonlinear least-square method. The power and exponential fit to the measured averaged ACF for different B2B and on-body channels are shown in Figs. 2 and 3 respectively. The models are fitted to the ACF decay till a moderate correlation coefficient of 0.5 to measure the optimum result. We measure the goodness-of-fit with the sum of squared errors of prediction (SSE) statistic [4]. A SSE value closer to 0 indicates that the model has a smaller random error component, and that the fit will be more useful for prediction. It can be seen from Figs. 2 and 3 that, both the on-body and B2B channels show a power-like decay for the autocorrelation function (SSE closer to 0). From that outcome, we can imply that the autocorrelation function of body-centric channels (B2B/on-body) has power-like decay, hence these channels possess long-range dependence.
average the $E[R/S]$ value from different groups of similar B2B/on-body links and measure the approximate Hurst exponent for specific type of B2B/on-body links. The results are shown in Fig. [4] where all of the links are giving a higher value of Hurst index (greater than 0.5). From these results it can be inferred that, body-centric channels (B2B/on-body) incorporate long-range dependence.

C. Long-memory and Stationarity

Beside statistical dependence, stationarity or wide-sense-stationarity (statistical properties, e.g., mean, auto-covariance, are invariant over time) is another important characteristic to estimate the predictability of a channel. From the long-memory outcome, it can be inferred that, both type of channels (on-body/B2B) are predictable. But we show in [6] that, B2B channels can possess wide-sense-stationarity (WSS) for certain period, whereas on-body channels depict non-stationary behavior. Hence, even if on-body channels can have long-memory, that memory is not useful because of the non-stationary behavior, which can produce spurious results.

IV. Conclusion

We show that, body-centric channels (on-body/B2B) can possess long-memory. However, only B2B links can be utilized for reliable predictive analysis due to their WSS property.

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