On Distributed Nonlinear Signal Analytics: Bandwidth and Approximation Error Tradeoffs

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Abstract—Analytics will be a part of the upcoming smart city and Internet of Things (IoT). The focus of this work is approximate distributed signal analytics. It is envisaged that distributed IoT devices will record signals, which may be of interest to the IoT cloud. Communication of these signals from IoT devices to the IoT cloud will require (lowpass) approximations. Linear signal approximations are well known in the literature. It will be outlined that in many IoT analytics problems, it is desirable that the approximated signals (or their analytics) should always over-predict the exact signals (or their analytics). This distributed nonlinear approximation problem has not been studied before. An algorithm to perform distributed over-predictive signal analytics in the IoT cloud, based on signal approximations by IoT devices, is proposed. The fundamental tradeoff between the signal approximation bandwidth used by IoT devices and the approximation error in signal analytics at the IoT cloud is quantified for the class of differentiable signals. Simulation results are also presented.

Index Terms—signal analysis, signal reconstruction, approximation methods, Internet of Things

I. INTRODUCTION

Signal representation using a finite number of coefficients is well known and is termed as source coding [1], sampling [2], and function approximation [3]. Analytics will be a part of the upcoming smart city and Internet of Things (IoT). It is envisaged that distributed signals may be recorded at the IoT devices [4]. At the IoT cloud, signal analytics from the recorded signals by many IoT devices is of interest.

Due to bandwidth constraint, each IoT device should send signal approximation for the intended signal analytics to the IoT cloud. A parsimonious signal approximation at each IoT device, that minimizes approximation error at the IoT cloud, is desired. The fundamental tradeoff between approximation bandwidth used by IoT devices and the approximation error in signal analytics at the IoT cloud is desirable.

Linear or mean-squared signal approximations are well known in the literature. An obvious method to approximate in a distributed manner is to compute the signals’ linear approximations using existing algorithms and communicate them [3], [5], [6], [7]. However, this method will not be applicable in certain nonlinear problems. The following envisaged smart city applications motivate distributed nonlinear signal analytics.

Smart meters: Consider the setup shown in Fig. 1. A smart city planner fixes smart meters (IoT devices) in each home. The smart meter records the (instantaneous) power signal consumed, and has to report it to the IoT cloud. The planner has to calculate the smallest sufficient supply capacity to meet the energy demand at all times. If \( f_1(t), \ldots, f_M(t) \) are the power consumption signals at various devices, then the planner is interested in \( \max\{f_1(t) + \ldots + f_M(t)\} \). However, due to bandwidth constraint IoT devices can only send approximations \( \hat{f}_1(t), \ldots, \hat{f}_M(t) \). The IoT cloud will compute \( \max\{\hat{f}_1(t) + \ldots + \hat{f}_M(t)\} \). For sufficient supply capacity calculation, it is required that

\[
\max\{\hat{f}_1(t) + \ldots + \hat{f}_M(t)\} \geq \max\{f_1(t) + \ldots + f_M(t)\}.
\]

In the above equation, the difference between the two quantities is the approximation error. Using an (over-predictive) envelope approximation, i.e., \( \hat{f}_i(t) \geq f_i(t), i = 1, \ldots, M \) is one approach to tackle this problem. In this case, the IoT cloud reconstructs the sum signal, \( \hat{s}(t) = \hat{f}_1(t) + \ldots + \hat{f}_M(t) \) and then reports \( \max\hat{s}(t) \) to the planner (see Fig. 1). The desired signal analytic and the associated approximation are both nonlinear.

Pollution control: Consider a smart city regulator, which has to report pollutant concentration (such as PM 2.5 levels). IoT devices with PM 2.5 sensors can be employed in the smart city, which record \( f_1(t), \ldots, f_M(t) \). To save bandwidth, each IoT device has to communicate its approximated pollution signal to the IoT cloud. The regulator can use air diffusion models (see [8]) to characterize the spatio-temporal evolution of the pollutant for the entire city. The regulator may want to provide...
a (pessimistic) pollution signal approximation, which requires over-predictive nonlinear signal analytics.

Renewable energy in a smart grid: Consider a smart city where solar panels generate electricity that returns to the power grid in the region. Let \( f_1(t), \ldots, f_M(t) \) be the renewable power generated as a function of time \( t \). These signals will be approximately communicated to the IoT cloud. The electricity planner will be interested in \( \min_i \{ f_1(t) + \ldots + f_M(t) \} \) to estimate an (under-predictive) envelope of the renewable power. This is also a nonlinear signal analytics problem.

With a focus towards over-predictive nonlinear signal analytics in an IoT, the following main results will be presented:

1) An algorithm using envelope approximations \(^9\) is presented for over-predictive signal analytics with IoT devices and cloud. Its simulation results are presented.

2) For the above algorithm, with Fourier basis, fundamental tradeoffs between approximation error and bandwidth will be analyzed for differentiable signals.

Prior Art: Linear signal analytics is well understood: distributed signals can be projected (approximated) in a linear basis and approximately communicated. However, this method will not apply to the above-mentioned applications. As far as we know, nonlinear signal analytics has not been studied. On the other hand, analytics of distributed scalars is well reported. Computation and reporting of symmetric functions of the scalar parameters (such as weighted average) has been studied \(^5\), \(^6\). Gossip based algorithms compute scalar functions in large networks, using linear fusion methods \(^7\), \(^10\).

Recently, there have been efforts towards big-data analytics in smart city/IoT \(^4\), \(^11\), \(^12\). To the best of our knowledge, these works do not address signal analytics where continuous-time signals are involved.

The paper is organized as follows. Section II explains the system background and problem formulation. An order optimal approximation algorithm for the over-predictive signal analytics is proposed in Section III. The bandwidth and error tradeoff for this scheme is analyzed in Section IV. Simulation setup and numerical results using electricity load data sets are presented in Section V.

II. BACKGROUND AND PROBLEM SETUP

IoT signals, their assumed smoothness properties, tradeoffs of interest, and problem formulation are discussed in this section.

A. Signal model and IoT description

Consider an IoT with \( M \) distributed IoT devices and an IoT cloud. We assume a cloud based IoT architecture with computing capability at the individual IoT devices \(^12\). The IoT cloud acts as a central server with the capacity to handle massive data arriving from a number of IoT devices. The IoT devices indexed \( 1, \ldots, M \) record signals \( f_1(t), \ldots, f_M(t) \) at various locations. Due to bandwidth constraint, the IoT devices individually communicate approximations \( \hat{f}_1(t), \ldots, \hat{f}_M(t) \) to the IoT cloud. Signal analytics are derived in the IoT cloud based on \( \hat{f}_1(t), \ldots, \hat{f}_M(t) \). Without loss of generality, it is assumed that \( f_1(t), \ldots, f_M(t) \) are recorded over the finite observation interval \( t \in [0, 1] \). The signals \( f_1(t), \ldots, f_M(t) \) will be assumed to be \( p \)-times differentiable in \( t \in [0, 1] \) for \( p \geq 1 \).

B. Fourier representation of IoT signals

Due to space constraints, this first exposition will use Fourier series basis for \( f_1(t), \ldots, f_M(t) \) on \([0, 1]\), with the constraint \( f_1(0) = f_1(1), i = 1, \ldots, M \) \(^8\). The Fourier series of \( f_1(t), \ldots, f_M(t) \) are given by

\[
\hat{f}_i(t) = \sum_{k=-\infty}^{\infty} a_i[k] \exp(j2\pi kt), \quad t \in [0, 1], i = 1, \ldots, M.
\]

The \( p \)-times differentiability of \( f_i(t), i = 1, \ldots, M \) implies that their Fourier coefficients decay polynomially in \( k \):

**Fact 2.1 (Sec 2.3, \(^12\))**: A signal \( f(t), t \in [0, 1] \), with \( f(0) = f(1) \), is \( p \)-times differentiable if its Fourier coefficient \( a[k] \) obey

\[
|a[k]| \leq \frac{C}{|k|^{p+1+\varepsilon}} \quad \text{for some } C, p, \varepsilon > 0.
\]

C. Approximation analysis and its definitions

For \( i = 1, \ldots, M \), bandlimited approximations of \( f_i(t) \) with Fourier coefficient \( a_i[k] \) are defined as

\[
\tilde{f}_i(t) = \sum_{k=-L}^{L} b_i[k] \exp(j2\pi kt) \quad \text{for } t \in [0, 1],
\]

where \( b_i[-L], \ldots, b_i[L] \) will be a function of \( a_i[k], k \in \mathbb{Z} \) chosen later according to specified criterion. Here, \( L \) the bandwidth of the approximate signals \( \tilde{f}_i(t) \).

Let the sum signal analytic of interest be \( s(t) = f_1(t) + \ldots + f_M(t) \). From \( s(t) \), for example, \( \max_t s(t) \) or \( \text{avg}\{s(t)\} \) can be obtained. The corresponding approximation obtained by the IoT cloud is \( \tilde{s}(t) = \tilde{f}_1(t) + \ldots + \tilde{f}_M(t) \). Let \( E := d(s(t), \tilde{s}(t)) \) be the approximation error according to some distance measure. For a given bandwidth \( L \), the overpredictive distributed signal analytics problem (see Section III) is:

\[
\min_{\tilde{f}_i(t)} E := d(s(t), \tilde{s}(t)) \quad \text{subject to } \tilde{s}(t) \geq s(t).
\]

For a signal \( f(t) \), the approximation \( \tilde{f}_{\text{env}}(t) \) such that \( \tilde{f}_{\text{env}}(t) \geq f(t) \forall t \in [0, 1] \) is called an envelope approximation \(^9\).

D. Distance measures of interest

For overpredictive approximation, we will construct envelope of the signal \( f(t) \) recorded by an IoT device \(^9\). While making envelope approximation \( \tilde{f}_{\text{env}}(t) \) of a signal \( f(t) \), a distance function is needed to capture the proximity of \( \tilde{f}_{\text{env}}(t) \) with \( f(t) \) \(^9\). In this work, the \( \mathcal{L}^1, \mathcal{L}^2 \) and \( \mathcal{L}^\infty \) distance measures will be used. Using the Fourier representations of

\(^1\) This end point symmetry constraint prevents Gibbs phenomenon during reconstruction \(^13\) of the signals, and it can be avoided by considering other basis (e.g., polynomials), but is omitted due to space constraints \(^13\).
where the above minimizations are over \( \hat{g} \) and \( f(t) \), and the envelope property \( f_{env}(t) \geq f(t) \) it can be observed that

\[
\|f_{env} - f\| = b(0) - a(0),
\]

\[
\|f_{env} - f\|_2^2 = \sum_{|k| \leq L} |b[k] - a[k]|^2 + \sum_{|k| > L} |a[k]|^2
\]

and,

\[
\|f_{env} - f\|_\infty \leq \sum_{|k| \leq L} |b[k] - a[k]| + \sum_{|k| > L} |a[k]|.
\]

In the above equation, the \( C_\infty \) distance is upper-bounded using an \( \ell_1 \) error between \( b[k] \) and \( a[k] \) in the sequence space. The approximation error in signal analytics \( E = d(s(t), \tilde{s}(t)) \) corresponding to the \( L^1, L^2, L^\infty \) distance measures will be denoted by \( SA_1, SA_2, SA_\infty \), respectively.

**E. Bandwidth and approximation error tradeoff**

The fundamental tradeoffs between the bandwidth parameter \( L \) and the approximation error \( E \) for \( L^p, p = 1, 2, \infty \) distance metrics will be presented, with the constraint that \( \tilde{s}(t) \geq s(t) \).

**III. OVERPREDICTIVE SIGNAL ANALYTICS**

Recall the smart city applications described in Fig. 1 with \( M \) IoT devices reporting the approximate signals observed to the IoT cloud. The signal analytics problem of interest are

\[
\min_{A} SA_q := \int_0^1 \| \tilde{s}(t) - s(t) \|^q dt \text{ subject to } \tilde{s}(t) \geq s(t) \quad (6)
\]

for \( q = 1, 2, \) and

\[
\min_{A} SA_\infty = \| \tilde{s} - s \|_\infty \text{ subject to } \tilde{s}(t) \geq s(t). \quad (7)
\]

where the above minimizations are over \( \tilde{f}_1(t), ..., \tilde{f}_M(t) \).

**A. Algorithm for overpredictive signal analytics in IoT**

It is assumed that each IoT device works in a distributed manner. To ensure \( \tilde{s}(t) \geq s(t) \), we propose that each IoT device can perform envelope approximation of its observed signal [9]. The following steps are proposed for obtaining a bandwidth-\( L \) approximation \( \tilde{s}(t) \) of \( s(t) \):

1) Each device \( i \) records its individual signal \( f_i(t) \), calculates its envelope \( f_{env}(t) \), and communicates its \((2L + 1)\) Fourier coefficients to the IoT cloud.

2) Using Fourier coefficients from each IoT device, the cloud calculates \( \tilde{f}_{env}(t) = \tilde{f}_{1, env}(t) + ... + \tilde{f}_{M, env}(t) \).

Signal envelope calculation in Step 1 above is outlined next. For \( L^1 \) distance (see (3)), it will be calculated as [9]

\[
\min b[0] - a[0] \text{ subject to } \| \Phi(t) \| \geq f(t) \quad (8)
\]

where \( \Phi(t) = [\exp(-2\pi Lt), ..., \exp(2\pi Lt)]^T \) and \( \vec{b} = (b[-L], ..., b[L])^T \) are the Fourier series coefficients of the envelope approximation. The above linear program with linear constraints is solvable efficiently [9]. For \( L^2 \) and \( L^\infty \), the cost function \( b[0] - a[0] \) is replaced by those in (4) and (5).

As \( L \) is increased, the envelopes \( \tilde{f}_{env}(t) \) become more proximal to their target \( f(t) \). It is expected that \( SA_1, SA_2, \) and \( SA_\infty \) will decrease as \( L \) increases. However, analyzing the dependence of \( SA_q, q = 1, 2, \infty \) versus \( L \) is difficult. Accordingly, naive envelope approximation [15] will be used to analyze fundamental bounds on their tradeoff. Since each IoT device approximates the signal in a distributed manner, the error in \( SA_q, q = 1, 2, \infty \) will increase with the number of IoT devices in the network as discussed in the next section.

**B. The naive envelope approximation**

First consider IoT device 1 in isolation. Let \( f_{1,proj}(t) \) be the orthogonal projection of \( f_1(t) \) on the span of \( \exp(i2\pi kt) \) for \( |k| \leq L \). Then \( f_{1,proj}(t) = \sum_{|k| \leq L} a[k] \exp(i2\pi kt) \). The naive envelope approximation scheme is as follows [15]:

\[
f_{1,env}(t) = f_{1,proj}(t) + C_0, \quad (9)
\]

where \( C_0 = \| f_1 - f_{1,proj} \|_\infty \). Using the triangle inequality,

\[
C_0 \leq \sum_{|k| > L} |a[k]| \leq \sum_{|k| > L} \frac{C}{|k|^p}, \quad p > 1. \quad (10)
\]

For \( p > 1 \) [16 Sec. 2.2] we can show that, \( C_0 = O \left( \frac{1}{L^{\frac{1}{p}}} \right) \).

**IV. NAIVE ENVELOPE APPROXIMATION ANALYSIS**

The main result is proved in this section.

**Theorem 4.1:** In [9] and [17], let \( SA_q \) be the optimal distance and \( SA'_q \) be the distance corresponding to the naive approximation in (9). There exist signals \( f_1(t), ..., f_M(t) \) such that for \( q = 1, 2, \infty \)

\[
C_1(q) \leq \frac{SA'_q}{SA_q} \leq C_2(q) \quad 0 < C_1(q) < C_2(q) < \infty. \quad (11)
\]

**Proof:** Using (10) and the triangle inequality on sum of signals and their envelopes, we determine bounds on \( SA_q \). They are tabulated in Table I where the result follows for \( q = 2, \infty \) by taking ratios of \( SA_q \) and \( SA'_q \). The steps are omitted due to space constraints. This result shows that the naive approximation is order optimal for the \( L^2 \) and \( L^\infty \) errors, if the IoT device signals are \( p \)-times differentiable.

The optimality of the naive envelopes for the \( SA_q \) distance holds for a signal class with the following properties: (i) the Fourier coefficients \( a[k] \) \( \geq 0 \), and (ii) \( f_1(t) \) is real and even, that is \( a[k] = a[-k] \). From these symmetry assumptions, it follows that \( b_1[k] = b_1[-k] \). Restricted to this signal class, the \( SA_1 \) envelope approximation is re-stated as:

\[
\arg \min b_1[0], \text{ subject to } b_1[k], |k| \leq L \quad (11)
\]

The above optimization can be shown to result in

\[
b_1[0] + 2 \sum_{1 \leq |k| \leq L} b_1[k] \cos(2\pi k t) \geq \sum_{|k| \leq L} a_1[k] e^{2\pi k t} \quad (11)
\]

It is noted that \( SA_1 \) and \( SA'_1 \) in Table I are comparable. The presented result is for 1 IoT devices. For \( M \) IoT devices, \( SA_1 \)
and $\text{SA}_\infty$ as well as $\text{SA}_1'$ and $\text{SA}_\infty'$ scale linearly with $M$. And $\text{SA}_2$ as well as $SA_2'$ scale quadratically with $M$. Their ratios remain the same as in $M = 1$.

**TABLE I**

**BOUNDS ON THE APPROXIMATION ERRORS**

| $L^q$ error metric | $\text{SA}_q$ | $\text{SA}_q'$ |
|---------------------|--------------|--------------|
| $q=1$               | $b_1[0] - a_1[0]$ | $\sum_{|k|>L} |a_1[k]|$ |
| $q=2$               | $\frac{2}{2p-1} \frac{1}{(L+1)^{2p-1}}$ | $\frac{2}{2p-1} \frac{1}{L^{2p-1}}$ |
| $q=\infty$         | $\frac{2}{p-1} \frac{1}{(L+1)^{p-1}}$ | $\frac{2}{p-1} \frac{1}{L^{p-1}}$ |

V. NUMERICAL SIMULATIONS

**Dataset Description:** Time series data of electricity loads (in KWhr) from Eastern and Western region grids of India are considered [17] (see Fig. 2). The time samples available at 30 minute intervals are interpolated using low pass projection on Fourier basis with 25 coefficients. For brevity of simulations a normalized amplitude scale is used. We also consider the pollution dataset from US EPA [18], consisting of the time-series variation of PM2.5 concentration in Denver. The hourly sampled data, for a duration of 1 day, is smoothened using lowpass filtering using 10 Fourier coefficients (see Fig. 3).

**Simulation setup and analysis:** Simulations for the approximation error and bandwidth tradeoffs are presented for grid load data in Fig. 2 [17]. The time series plots for individual load variation are shown in Fig. 2 (a). The sum signal envelope is reconstructed at the IoT Cloud with $(2L+1) = 7$ Fourier coefficients (see Fig. 2(b)). The convergence of the estimate $\hat{s}(t)$ to $s(t)$ with increasing $L$ is studied in Fig. 2(c). It is observed that the maxima of the sum signal is eventually tracked under each of the cost functions. The oscillations in the error plot (see Fig. 2(c)) are the artifacts of the distributed and nonlinear nature of the approximation algorithm. At any IoT device, the maximum (nonlinear) of the signal is tracked with uniformly decreasing error. However, since each device independently (i.e., in a distributed manner) reports the approximations to the IoT cloud, the errors do not die down uniformly, but with occasional rise. Fig. 2(d) captures the bandwidth-

2United States Environmental Protection Agency
error tradeoff for the three distance measures considered in the paper. The performance of the naïve approximation scheme is seen to coincide with that of the $L^\infty$ error optimization. This is attributed to the relaxation of the $L^\infty$ cost in terms of the coefficients as discussed in [5].

We analyze the gap between the upper and lower signal envelopes using the pollution dataset [13] (Fig. 3). We observe that the average gap between the envelopes decays with increasing value of $L$. It is to be noted that the lower envelope is negative in certain time intervals. In Fig. 3(d) we analyze the error in time estimate of the peak pollutant concentration, $t_{\text{max}}$. The estimates approach the true value of signal analytic (ie $t_{\text{max}}$) eventually with growing bandwidth parameter $L$.

Energy consumption in IoT Device and IoT Cloud : By using IoT energy consumption data, a comparison of different IoT energy requirements are shown in Fig. 4 [19]. For a communication mode with $E_b$ energy/bit requirement and $B_r$ bits/coefficient, the proposed envelope scheme requires $(2L + 1)E_bB_r$ energy units per device. The computing energy requirement (see Fig. 2(d)) is determined by counting the number of floating point operations (FLOP) in MATLAB to execute the optimization algorithm at the device. The conversion of FLOP to equivalent Joules is performed with respect to a 100 GFLOP/sec/W processor (see TI C667x processor [20]). It is observed that the communication and computation energy expenditure is observed to linear increase with the number of approximation coefficients.

![Diagram](image)

Fig. 4. Energy expenditure at IoT device for communication and computing. Simulation parameters - $E_b = 0.4279$ nJ/bit for Ethernet, 5.25 nJ/bit for WiFi, bits per coefficient $B_r = 32$ bits and 100 GFLOPS/W processor.

VI. CONCLUSIONS

Distributed nonlinear signal analytics was introduced for the first time. It was observed that in applications such as energy distribution, signal observed by IoT devices should be subjected to envelope approximation. An algorithm for over-predictive nonlinear signal analytics in the IoT cloud was developed in this work, by using the envelope approximation technique. The fundamental tradeoff between approximation error in signal analytics ($\mathcal{SA}_q$, $q = 1, 2, \infty$) and the bandwidth parameter $L$ was established. It was observed that this tradeoff depends on the smoothness of signals at the IoT devices. Simulation results were presented for load data collected from two power grids. Envelope approximation schemes using polynomial and wavelet basis are proposed as a future extensions.

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