KTH Electrical Engineering

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MATTIAS ANDERSSON, ALI A. ZAIDI, NIKLAS WERNERSSON, AND MIKAEL SKOGLUND

Stockholm 2011

Communication Theory
School of Electrical Engineering
Kungliga Tekniska Hgskolan

Nonlinear Distributed Sensing for Closed-Loop Control Over Gaussian Channels

Mattias Andersson*, Ali A. Zaidi*, Niklas Wernersson†, and Mikael Skoglund*
*School of Electrical Engineering and the ACCESS Linnaeus Center
Royal Institute of Technology (KTH), Stockholm, Sweden
†Ericsson Research, Stockholm, Sweden

***Abstract*—A scenario of distributed sensing for networked control systems is considered and a new approach to distributed sensing and transmission is presented. The state process of a scalar first order linear time invariant dynamical system is sensed by a network of wireless sensors, which then instantaneously transmit their measurements to a remotely situated control unit over parallel Gaussian channels. The control unit aims to stabilize the system in mean square sense. The proposed non-linear delay-free sensing and transmission strategy is compared with the well-known amplify-and-forward strategy, using the LQG control cost as a figure of merit. It is demonstrated that the proposed non-linear scheme outperforms the best linear scheme even when there are only two sensors in the network. The proposed sensing and transmission scheme can be implemented with a reasonable complexity and it is shown to be robust to the uncertainties in the knowledge of the sensors about the statistics of the measurement noise and the channel noise.**

***Index Terms*—Networked control systems, Wireless sensor networks, Source–channel coding, Distributed sensing, Linear Quadratic Gaussian Control, State estimation, Mean square stabilization.**

I. INTRODUCTION

We consider a scenario where a linear plant is monitored by a wireless sensor network, for the purpose of closed-loop control of the plant's state. The state is observed in noise by several sensors that convey their measurements over wireless channels. The transmitted signals are received in Gaussian noise by a central sink node. The sink computes an estimate of the plant's state, and this estimate is then used by a controller for actuation at the input of the plant. The overall goal of the system is to stabilize the plant and minimize the LQG cost.

Control over band-limited and noisy channels has become an increasingly active field of research over the past decade. A nice summary of the present status of the research in this area is given in [1]. Early important contributions on control under under communication constraints are given in [2]–[12] (see also the references in [1]). Some of the important and recent contributions on the problem of closed-loop control over various types of Gaussian channels include [13]–[23]. Recent work on joint design of source–channel coding and control is presented in [24].

For the problem of closed-loop control of a scalar valued system over a Gaussian channel in the presence of a single sensor node, a linear sensing strategy has been shown to be optimal by Bansal and Başar in [2]. Further in [25], Yüksel and Tatikonda showed via a counter-example that linear schemes are not optimal in general for multi-sensor setups. In [26] and [27], the authors have studied a network of cascaded sensors and have shown via counter-examples that linear policies are not optimal even when there exist two sensors in cascade. These recent results on non-optimality of linear sensing policies provide motivation to study non-linear strategies for distributed sensing in control applications.

In this paper, we propose to use a class of non-linear sensor mappings for the problem of control over parallel Gaussian channels using multiple sensors. This paper is inspired by our earlier work on distributed joint-source channel coding [28]. The proposed scheme is instantaneous (i.e., delay-free) and it can be implemented with a reasonable complexity. Furthermore, the proposed scheme has been shown to be insensitive to the uncertainty in the knowledge of the sensors about the powers of the measurement and the channel noises, which is generally a crucial aspect in designing practical systems.

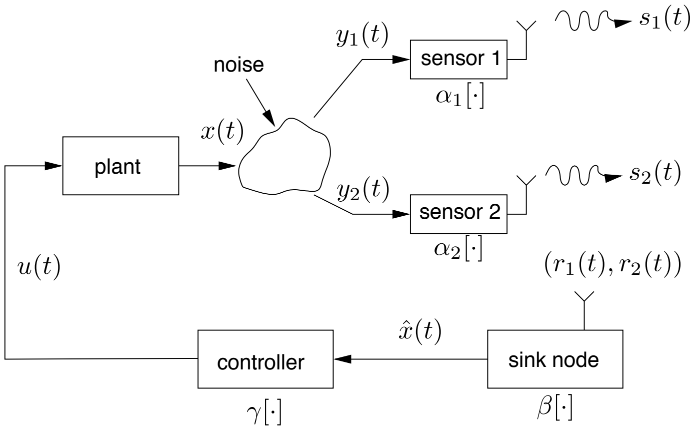

Fig. 1. A closed-loop control system with state measurements transmitted over wireless channels.

II. PROBLEM FORMULATION

Consider the system illustrated in Figure 1. The box labeled "plant" is a scalar discrete-time linear system, modeled as

$$x(t+1) = ax(t) + u(t) + v(t), \tag{1}$$

where $a > 0$ is a real-valued parameter, $x(t)$ is the *state* of the system, $u(t)$ is the *control signal*, and $v(t)$ is the *process*

This work was supported in part by the European Commission through the FP7 project FeedNetBack (co-design for networked control systems).

noise, all of them real valued and at discrete time $t \geq 0$. The initial state $x(0)$ is an unknown random variable drawn according to a zero-mean Gaussian distribution with variance σ_x^2. The process noise $v(t)$ is assumed to be i.i.d. zero-mean Gaussian distributed. The state $x(t)$ is observed in noise by the two sensors, resulting in the following sensor input signals

$$y_i(t) = x(t) + n_i(t), \quad i = 1, 2,$$

where $n_1(t)$ and $n_2(t)$ are two i.i.d. mutually independent measurement noise components, which have Gaussian distributions with zero means and variances $\sigma_{n,1}^2$ and $\sigma_{n,2}^2$, respectively.

The sensor measurements are conveyed wirelessly to a sink node. Independently of each-other, the two sensors transmit the real-valued signals $s_1(t)$ and $s_2(t)$, via two memoryless mappings $\alpha_i : \mathbb{R} \times \mathbb{N} \mapsto \mathbb{R}$ for $i = 1, 2$, such that

$$s_i(t) = \alpha_i[y_i(t), t], \quad i = 1, 2,$$

subject to the following power constraints:

$$E[s_i^2(t)] \leq P_i, \; i = 1, 2. \tag{2}$$

The two transmitted signals $s_i(t)$, $i = 1, 2$, are received at the sink node as

$$r_i(t) = s_i(t) + w_i(t), \quad i = 1, 2, \tag{3}$$

where $w_i(t)$, $i = 1, 2$, are independent and i.i.d. zero-mean Gaussian with (equal) power $N_0/2$. Note that we assume orthogonal channels from the sensors to the sink node, therefore there is no interference between the two received signals (i.e., we have two parallel Gaussian channels from the sensors to the sink node). In general, the current and all the previously received values for the received vector $\mathbf{r}(t) = (r_1(t), r_2(t))$ can be used by the sink node to compute the state-estimate $\hat{x}(t)$, as

$$\hat{x}(t) = \beta[\mathbf{r}_0^t],$$

where $\mathbf{r}_0^t = (\mathbf{r}(0), \ldots, \mathbf{r}(t))$. As can be noted, the triple $(\alpha_1, \alpha_2, \beta)$ forms a "distributed source–channel code" for transmission of noisy measurements over Gaussian channels (c.f., [28] and references therein). When the decoder (sink node) has computed $\hat{x}(t)$, the estimate is fed to the controller which then forms

$$u(t) = \gamma[\hat{x}(t)],$$

as in [24] (see also, e.g., [1], [29]).

The goal of the system is to minimize the following finite horizon quadratic cost function:

$$L_T = E\left\{\sum_{t=1}^{T} x^2(t) + \rho u^2(t-1)\right\}, \tag{4}$$

where the expectation is taken over the initial state $x(0)$, the process noise $v(t)$, the measurement noise $n_i(t)$, and the transmission noise $w_i(t)$. The minimization is done subject to the power constraint, $E[s_i^2(t)] \leq P_i$. The purpose of the system is hence to minimize the state-evolution, departing from the initial state $x(0)$, in the sense of minimizing L_T. The real parameter $\rho \geq 0$ penalizes large values of $u(t)$.

The Controller

In the cases where $x(t)$ can be observed directly (no measurement noise), or when the sensor mappings $\alpha_i[\cdot]$ are linear, it is optimal to use a linear controller

$$u(t) = -\ell_t \hat{x}(t), \tag{5}$$

where ℓ_t can be computed given the system model (1), observation equation (3) and objective function (4) [29]. For simplicity, and also to make it easier to isolate the gains achievable by the new class of sensors/transmitters, we choose to use the linear controller also in our proposed system. Note that in general, splitting the receiver–controller into separate estimation (computing $\hat{x}(t)$) and linear control is not without loss [1], [24].

III. Sensing and Transmission

In this section we propose a non-linear sensing and transmission scheme and heuristically motivate the potential gains that this scheme can deliver. For the sake of comparison we use the following linear scheme as a reference.

A. Baseline scheme

The reference scheme is the well-known amplify-and-forward strategy, in which the sensor nodes amplify the received signals subject to average power constraints and then transmit them to the sink node. The transmitted signals from the two sensors are given by

$$s_1(y_1(t)) = \eta_{1,t} y_1(t), \tag{6}$$

$$s_2(y_2(t)) = \eta_{2,t} y_2(t), \tag{7}$$

where η_t is chosen such that the power constraint (2) is fulfilled. The optimal decoder for this encoding scheme is a Kalman filter [29].

B. Potential Gains from Non-linear Sensing

We now heuristically motivate the use of the non-linear scheme that we will present in the sequel. Keeping the linear controller we should be able to get better performance by replacing the linear encoders $\alpha_i[\cdot]$ with encoders that try to minimize the distortion between $x(t)$ and $\hat{x}(t)$. In order to do so we need to design the encoders α_1 and α_2, as well as the decoder β, taking into account that the sensor measurements $y_1(t)$ and $y_2(t)$ are dependent since they both contain the common variable $x(t)$. Source and channel coding for correlated variables over orthogonal channels has been widely studied, see e.g. [28], [30]–[33]. The main result of these papers is that due to the dependency between the variables $y_1(t)$ and $y_2(t)$, the encoders α_1 and α_2 need to be designed jointly in order to achieve optimal performance. Furthermore, using linear encoders according to (6) and (7) will in general be suboptimal.

In the problem setting we are considering, improving the estimation of $x(t)$ in the MSE sense, i.e. lowering $E[(x(t) - \hat{x}(t))^2]$, will allow a better and more efficient actuation by the control value $u(t)$ which in turn should lead to decreasing $E[x^2(t+1)]$. Furthermore, due to the power decrease in

$x(t+1)$ we will be able to transmit with stronger output gain η_t which then gives a better estimate of $x(t+1)$. Hence, allowing optimal (in the sense of minimizing $E[(x(t)-\hat{x}(t))^2]$) encoding and decoding functions at any time t will lower (4), at least for $\rho = 0$. Hence, we can draw a conclusion that there is a potential gain in considering nonlinear encoding functions α_1 and α_2.

C. The Proposed Scheme

In [28] a nonlinear scheme for low delay source–channel coding of correlated variables over orthogonal channels was proposed. The scheme was shown to have a better performance than the linear encoding scheme. Influenced by this scheme we propose the following source–channel code for the problem we are considering:

$$s_1(y_1(t)) = \eta_{1,t} y_1(t), \tag{8}$$

$$s_2(y_2(t)) = \eta_{2,t}\left(y_2(t) - \Delta_t \left\lfloor \frac{y_2(t)}{\Delta_t} \right\rceil\right), \tag{9}$$

where $\lfloor\cdot\rceil$ denotes rounding to the nearest integer, η_t controls the power usage and Δ_t controls the length of each period in the periodic sawtooth function $s_2(y_2(t))$. The procedure of choosing Δ_t will be presented shortly.

Let us now analyze the resulting power consumption. Note that the power used by the nonlinear encoding function in (9) will be less than the power used by the linear encoding function in (7). Hence, using the nonlinear encoding functions will save power. We define the normalized average power consumption at time t as

$$P(\mathbf{\Delta}_0^t, t) = \frac{1}{2\eta_t^2}(E[s_1(t)^2] + E[s_2(t)^2]). \tag{10}$$

By performing timesharing the sensors could use the linear encoding function for half of time and then use the nonlinear encoding functions the rest of the time. Hence, $P(\mathbf{\Delta}_0^t, t)$ can be seen as the average power used by each sensor at time t if $\eta_t = 1$.

D. Computing the State-Estimate

In order to compute the state estimate $\hat{x}(t)$ at the sink node based on the measurements $\mathbf{r}_0^t$, we take the following steps as depicted in Figure 2.

1) Compute estimates $\tilde{x}(0|t), \ldots, \tilde{x}(t|t)$ of $x(0), \ldots, x(t)$ based on the previous estimate $\hat{x}(t-1)$ and $r_1(t)$ using a Kalman filter (Kalman Filter 1 in the figure).
2) Assume that $|(\tilde{x}(s|t) - y_2(s) - w_2(s))/\eta_s| \le \Delta_s/2 \ \forall s$ and compute the Maximum Likelihood estimates $\hat{y}_2(s)$ as (cf. ML decoder in Fig. 2):
$$\hat{y}_2(s) = \text{argmin}_{y(s)\in\mathcal{Y}}(s_2(y(s)) - r_2(s))^2), \tag{11}$$
where $\mathcal{Y} = \{y(s) : |\tilde{x}(s|t) - y(s)| \le \eta_s\Delta_s/2\}$.
3) Finally assume that the estimates $\hat{y}_2(s)$ had been linearly encoded (multiplied by η_0^t) and find the estimate $\hat{x}(t)$ from a Kalman filter using $\{(r_1(0), \eta_0\hat{y}_2(0)), \ldots, (r_1(t), \eta_t\hat{y}_2(t))\}$ and $\{u(0), \ldots, u(t-1)\}$ as input (Kalman Filter 2 in the figure).

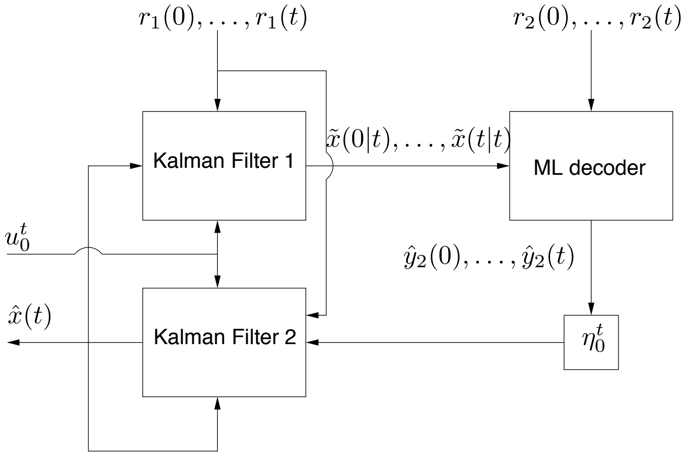

Fig. 2. Decoder for nonlinear encoding functions.

The above procedure will in general not produce the optimal minimum mean squared-error (MMSE) estimate $E[x(t)|\mathbf{r}_0^t]$, but can be implemented with a reasonable complexity. We note that the optimal MMSE estimator does not appear to be practical in our scenario.

E. Choosing Δ_t.

We propose the following procedure to choose the parameters $\{\Delta_t\}$ in the sawtooth sensor mapping:

- For time step $t = 0$, we choose Δ_0 as to minimize $E[(\hat{x}(0) - x(0))^2]$. This is done using methods similar to the ones in [28].
- For time step $t = 1$, we fix Δ_0 to the value found in step 1, and simulate the system up to $t = 1$ for different values of Δ_1. We then choose the value of Δ_1 that minimizes $E[(\hat{x}(1) - x(1))^2]$.
- Similarly for any time $t = s$, we fix $\Delta_0, \ldots, \Delta_{s-1}$ to the values found in the previous steps and simulate the system up to $t = s$ for different Δ_s. We then choose the Δ_s that minimizes $E[(\hat{x}(s) - x(s))^2]$.

IV. Performance Analysis

Let $z(t)$ denote the estimation error in $\hat{x}(t)$, i.e.

$$\hat{x}(t) = x(t) + z(t). \tag{12}$$

Using this with (1) and (5) we get

$$\begin{aligned} x(t) &= ax(t-1) + u(t-1) + v(t-1) \\ &= (a - \ell_{t-1})x(t-1) - \ell_{t-1}z(t-1) + v(t-1). \end{aligned} \tag{13}$$

Studying the cost function (4) for the case $\rho = 0$ we get the optimal choice $\ell_t = a$. We can then write L_T as

$$L_T = E\left[\sum_{t=1}^{T} x(t)^2\right] = E\left[\sum_{t=1}^{T}(-az(t-1) + v(t-1))^2\right] = E\left[\sum_{t=1}^{T}\left(a^2 z(t-1)^2 + v(t-1)^2\right)\right] = \sum_{t=1}^{T}\left(a^2\sigma_{z(t-1)}^2 + \sigma_v^2\right). \tag{14}$$

From this we note that the performance of the system will depend on the two terms $a^2\sigma^2_{z(t-1)}$ and σ^2_v. The second term σ^2_v arises from the process noise which we will not be able to affect. The first term $a^2\sigma^2_{z(t-1)}$ arises from the estimation error $z(t)$. Hence, improving the estimation of $x(t)$, i.e. lowering $\sigma^2_{z(t)}$, will lower the value of the cost function as previously stated. However, one might also suspect that the induced distribution of $z(t-1)$ affects the cost L_T since it changes the distribution of $x(t)$. This is only implicitly true, the created MSE $E[(x(t)-\hat{x}(t))^2]$ of the proposed scheme in (8)–(9) will, approximately, not depend on the distribution of $x(t)$ given a fixed system s_1 and s_2, see [28]. However, the distribution of $x(t)$ will affect $P(\mathbf{\Delta}^t_0, t)$ which in turn will affect the scaling parameter of the output and this parameter naturally affects the MSE.

The impact of the process noise v_t on our system is interesting. A high process noise variance σ^2_v will directly make the objective function larger as seen above, but it will also make the correlation between the two sensor measurements larger. If we have no process noise then $x(t) = -az(t-1)$ which, given good encoders and decoders, will be small. Thus the impact of measurement noise will be higher, taking away the correlation between $y_1(t)$ and $y_2(t)$ and most of the benefits of joint source–channel coding. For low process noise we would thus expect that using non-linear encoders at time $t = 0$ and linear encoders for the other time steps (corresponding to $\Delta_t = \infty$ for $t > 0$) will be optimal.

The impact of the channel noise variances on the performance was studied in [28]. There it was shown that either low or high σ^2_w will lead to a linear system working as well as the nonlinear.

In order to verify our claims, we perform numerical simulations for different values of the system parameters.

Numerical Simulations:

In Figures 3–5 we present results from three simulations. For all simulations, we choose the system parameter $a = 1.2$, the initial state variance $\sigma^2_x = 5$, the time-horizon $T = 3$ and in the objective function (4) we have set $\rho = 0$. Further we only consider the cases with equal power constraints at the sensors and equal measurement noise variances, i.e., $\sigma^2_{n,1} = \sigma^2_{n,2}$ and $P_1 = P_2$. All optimized values for Δ^{T-1}_0 can be found in Table I.

The results from the first simulation are shown in Figure 3. Here we vary the channel noise variance $N_0/2$ while keeping the other parameters fixed. For the optimized nonlinear and the linear curves we have optimized the encoders and decoder for the actual SNR used in the simulation. For the mismatched nonlinear curve we used the encoder optimized for SNR = 9 dB, but the decoder used the true SNR of the channel. This was done in order to see how robust the encoders are to SNR mismatch. We see that the nonlinear system gives a power gain over the linear system with up to 2 dB, and also that the system is very robust to SNR mismatch.

In the second simulation we use the same parameters as in the first simulation, but here the process noise variance is $\sigma^2_v = 3$. The mismatched system is again optimized for SNR = 9 dB. For this simulation we also see a 2 dB gain, and again the system is robust to SNR mismatch.

The results from the third simulation are shown in Figure 5. Here we keep the channel noise variance $N_0/2$ fixed, while instead varying the measurement noise variance σ^2_n. As in the first two simulations we show results for both optimized and mismatched Δ^{T-1}_0. The mismatched Δ^T_0 were optimized for $\sigma^2_n = 0.16$.

TABLE I
OPTIMIZED VALUES OF Δ^T_0 FOR DIFFERENT CHOICES OF SYSTEM AND CHANNEL PARAMETERS.

SNR (dB)	σ^2_n	σ^2_v	Δ_0	Δ_1	Δ_2
6	0.001	1	10.6	6.2	4.2
9	0.001	1	5.6	2.4	2.4
12	0.001	1	4	1.8	1.8
15	0.001	1	3	1.4	1.4
18	0.001	1	2.2	1	1
21	0.001	1	1.6	1	1
6	0.001	3	10.5	7.5	6.75
9	0.001	3	5.5	4.5	4.5
12	0.001	3	4	3	3
15	0.001	3	3	2.5	2.5
18	0.001	3	2.25	1.75	1.75
21	0.001	3	1.75	1.25	1.25
10	0.01	0	5	∞	∞
10	0.06	0	5.6	∞	∞
10	0.11	0	6.2	∞	∞
10	0.16	0	6.8	∞	∞
10	0.21	0	7.2	∞	∞
10	0.26	0	7.8	∞	∞
10	0.31	0	8.4	∞	∞
10	0.36	0	8.8	∞	∞
10	0.41	0	9.2	∞	∞
10	0.46	0	9.8	∞	∞
10	0.51	0	10.2	∞	∞

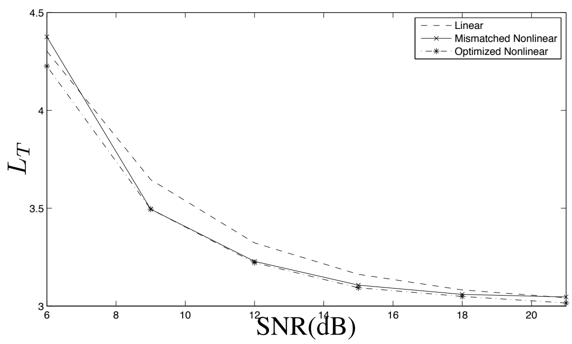

Fig. 3. Systems with $\sigma^2_n = 0.001$ and $\sigma^2_v = 1$

V. CONCLUSIONS

We have suggested a distributed source-channel code to be used in a closed-loop control system with two sensors measuring the plant's state. The proposed sensing and transmission scheme is delay-free, robust to the knowledge of noise statistics at the sensors, and can be implemented with reasonable complexity. The non-linear sensing has been shown to outperform the best linear strategy. Intuitively, this scheme

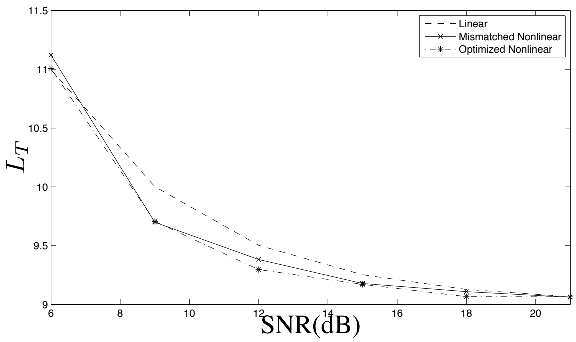

Fig. 4. Systems with $\sigma_n^2 = 0.001$ and $\sigma_v^2 = 3$

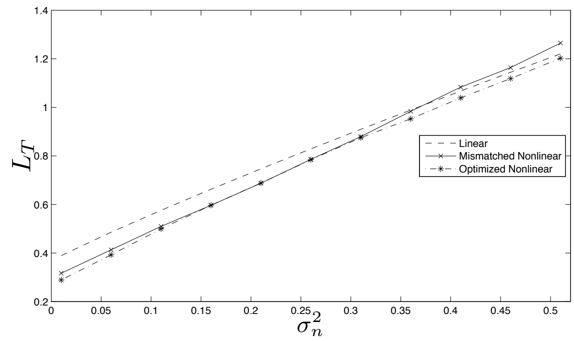

Fig. 5. System with SNR = 10 dB and $\sigma_v^2 = 0$

can be easily extended to an arbitrary number of sensors by employing a linear mapping at the first sensor node and sawtooth mappings at the remaining sensor nodes with successively decreasing time periods Δ_t. How the number of sensor nodes will affect the system performance compared to the best linear scheme is yet to be studied.

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