Analysis of Newton-Raphson Consensus for multi-agent convex optimization under asynchronous and lossy communications

Ruggero CarliGiuseppe NotarstefanoLuca SchenatoDamiano Varagnolo

CDC 2015 - Osaka

December 14, 2015







Joint work with...



Ruggero Carli Univ. of Padova



Giuseppe Notarstefano Univ. of Lecce



Luca Schenato Univ. of Padova

why distributed optimization?

Example: distributed localization

Range-bearing measurements:



Example: distributed localization

Range-bearing measurements:



Definitions

•
$$x_i \in \mathbb{R}^2$$
 = position of robot *i*

- $\mathbf{x} = (x_1, \dots, x_N) \in \mathbb{R}^{2N}$ = summary of all the positions
- *z_{ij}* ∈ ℝ² = *x_i* − *x_j* + *noise* = noisy measurement of the distance between *i* and *j*

Example: distributed localization

Range-bearing measurements:



Definitions

•
$$x_i \in \mathbb{R}^2 = \text{position of robot } i$$

•
$$\boldsymbol{x} = (x_1, \dots, x_N) \in \mathbb{R}^{2N} =$$
 summary of all the positions

z_{ij} ∈ ℝ² = *x_i* − *x_j* + *noise* = noisy measurement of the distance between *i* and *j*

Problem

$$oldsymbol{x}^* = rgmin_{\widetilde{oldsymbol{x}} \in \mathbb{R}^{2N}} \sum_i \sum_{j \in \mathcal{N}_i} \|\widetilde{x}_i - \widetilde{x}_j - z_{ij}\|^2$$

what are the challenges?

- asynchronous communications
- broadcast communications
- no channel feedback

synchronous communications:

ADMM (Bertsekas 1997, Boyd 2010, He 2011, Deng 2011, Johansson 2008, Mota 2012,...)

synchronous communications:

ADMM (Bertsekas 1997, Boyd 2010, He 2011, Deng 2011, Johansson 2008, Mota 2012,...)

asynchronous communications with perfect channel feedback: ADMM with symmetric gossip (Wei Ozdaglar 2012, Jakovetic 2011, ...)

synchronous communications:

ADMM (Bertsekas 1997, Boyd 2010, He 2011, Deng 2011, Johansson 2008, Mota 2012,...)

asynchronous communications with perfect channel feedback: ADMM with symmetric gossip (Wei Ozdaglar 2012, Jakovetic 2011, ...)

asynchronous communications without perfect channel feedback: Distributed quadratic programming, i.e.,

$$f(x) = \sum_{i} f_i(x) \qquad f_i(x) = (a_i x - b_i)^2$$

synchronous communications:

ADMM (Bertsekas 1997, Boyd 2010, He 2011, Deng 2011, Johansson 2008, Mota 2012,...)

asynchronous communications with perfect channel feedback: ADMM with symmetric gossip (Wei Ozdaglar 2012, Jakovetic 2011, ...)

asynchronous communications without perfect channel feedback: Distributed quadratic programming, i.e.,

$$f(x) = \sum_{i} f_i(x) \qquad f_i(x) = (a_i x - b_i)^2$$

asynchronous communications without perfect channel feedback: *in general ???*

In this work

From distributed quadratic programming:

$$f(x) = \sum_{i} (a_{i}x - b_{i})^{2} \quad \Rightarrow \quad x^{*} = \frac{\frac{1}{N}\sum_{i} a_{i}b_{i}}{\frac{1}{N}\sum_{i} a_{i}^{2}}$$

-

to \mathcal{C}^2 functions with bounded second derivative:

$$f_i(x) \in \mathcal{C}^2$$
 $f_i''(x) > c$ \Rightarrow $x^* = \arg\min_{\widetilde{x}} \sum_i f_i(\widetilde{x})$

In this work

From distributed quadratic programming:

$$f(x) = \sum_{i} (a_{i}x - b_{i})^{2} \quad \Rightarrow \quad x^{*} = \frac{\frac{1}{N}\sum_{i} a_{i}b_{i}}{\frac{1}{N}\sum_{i} a_{i}^{2}}$$

-

to \mathcal{C}^2 functions with bounded second derivative:

$$f_i(x) \in \mathcal{C}^2$$
 $f_i''(x) > c$ \Rightarrow $x^* = \arg\min_{\widetilde{x}} \sum_i f_i(\widetilde{x})$

building block: still average consensus

how to compute an average?

synchronous communications (2):

synchronous gossip consensus (Fagnani Zampieri 2008, Boyd et al. 2006, ...)

synchronous communications (2):

synchronous gossip consensus (Fagnani Zampieri 2008, Boyd et al. 2006, ...)

synchronous communications (2):

synchronous gossip consensus (Fagnani Zampieri 2008, Boyd et al. 2006, ...)

asynchronous communications with perfect channel feedback: ratio consensus (Bénézit et al. 2010)

asynchronous communications without perfect channel feedback: robust ratio consensus (Dominguez-Garcia et al. 2011)

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$

$$P(k) = \begin{bmatrix} 1 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$(4)$$

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$

$$P(k) = \begin{bmatrix} 1 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$F(k) = \begin{bmatrix} 1 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$

$$P(k) = \begin{bmatrix} 1 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$

$$P(k) = \begin{bmatrix} 1 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1/4 & 1 \end{bmatrix}$$

$$x_1 \leftarrow x_1 + x_4 + x_4 + x_4 + x_4 + x_5 \leftarrow x_5 + x_5 + x_4 + x_5 \leftarrow x_5 + x_5 \leftarrow x_5 + x_4 + x_5 \leftarrow x_5 + x_5 \leftarrow x_5 + x_5 \leftarrow x_5 + x_5 \leftarrow x_5 + x_5 + x_5 \leftarrow x$$

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$

$$P(k) = \begin{bmatrix} 1 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix}$$

$$\begin{cases} x_i(k) \to \beta_i(k) \sum_j x_i(0) \\ y_i(k) \to \beta_i(k) \sum_j y_i(0) \end{cases}$$

asynchronous communications with perfect channel feedback (Bénézit et al. 2010)

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$

$$P(k) = \begin{bmatrix} 1 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\begin{cases} x_i(k) \to \beta_i(k) \sum_j x_i(0) \\ y_i(k) \to \beta_i(k) \sum_j y_i(0) \end{array} \implies z_i(k) := \frac{x_i(k)}{y_i(k)} \to \frac{\sum_i x_i(0)}{\sum_i y_i(0)} = \frac{1}{N} \sum_i \theta_i$$

11

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$

$$P(k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\mathbf{F}(k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$
$$P(k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$



- $b_{i,x}$: total cumulative mass of x_i
- $\beta_{i,x}^{(j)}$: j's local estimate of $b_{i,x}$

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$

$$P(k) = \begin{bmatrix} 1 & 0 & \mathbf{0} & \mathbf{0} & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

- $b_{i,x}$: total cumulative mass of x_i
- $\beta_{i,x}^{(j)}$: j's local estimate of $b_{i,x}$

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$

$$P(k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$4$$

$$x_5 \leftarrow x_5 + b_{x,4} - \beta_{x,4}^{(3)}$$

$$y_5 \leftarrow y_5 + b_{y,4} - \beta_{y,4}^{(3)}$$

- $b_{i,x}$: total cumulative mass of x_i
- $\beta_{i,x}^{(j)}$: j's local estimate of $b_{i,x}$

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$
$$P(k) = \begin{bmatrix} 1 & 0 & 0 & \mathbf{0} & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$



- $b_{i,x}$: total cumulative mass of x_i
- $\beta_{i,x}^{(j)}$: j's local estimate of $b_{i,x}$

$$\begin{cases} \mathbf{x}(k+1) = P(k)\mathbf{x}(k) \\ x_i(0) = \theta_i \\ \mathbf{y}(k+1) = P(k)\mathbf{y}(k) \\ y_i(0) = 1 \end{cases}$$
$$P(k) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 1/4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1/4 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

- $b_{i,x}$: total cumulative mass of x_i
- $\beta_{i,x}^{(j)}$: j's local estimate of $b_{i,x}$



distributed Newton-Raphson

Initialization

$$f_i(x) = rac{1}{2} \left(a_i x - b_i
ight)^2 \quad \Rightarrow \quad \left\{ egin{array}{cc} y_i & \leftarrow a_i b_i \\ z_i & \leftarrow a_i^2 \end{array}
ight.$$

Initialization

$$f_i(x) = rac{1}{2} (a_i x - b_i)^2 \quad \Rightarrow \quad \left\{ egin{array}{cc} y_i &\leftarrow a_i b_i \\ z_i &\leftarrow a_i^2 \end{array}
ight.$$

transmitting node

$$y_i \leftarrow \frac{1}{|\mathcal{N}_i^{\text{out}}| + 1} y_i$$
$$z_i \leftarrow \frac{1}{|\mathcal{N}_i^{\text{out}}| + 1} z_i$$
$$x_i \leftarrow (1 - \varepsilon) x_i + \varepsilon \frac{y_i}{z_i}$$
$$b_{i,y} \leftarrow b_{i,y} + y_i$$
$$b_{i,z} \leftarrow b_{i,z} + z_i$$

receiving node

$$y_{j} \leftarrow y_{j} + b_{i,y} - \beta_{i,y}^{(j)}$$
$$z_{j} \leftarrow z_{j} + b_{i,z} - \beta_{i,z}^{(j)}$$
$$x_{j} \leftarrow (1 - \varepsilon)x_{j} + \varepsilon \frac{y_{j}}{z_{j}}$$
$$\beta_{i,y}^{(j)} \leftarrow b_{i,y}$$
$$\beta_{i,z}^{(j)} \leftarrow b_{i,z}$$

Convergence properties

Assumptions

- fixed, strongly connected and directed network
- exponential i.i.d. waiting times between local broadcasts
- $\mathbb{P}\left[\text{unsuccessful communications}\right] < 1$
- ε ∈ (0, 1]

Proposition

$$\mathbb{P}\left[\lim_{t\to\infty}x_i(t)=x^*\right]=1\qquad\forall i$$

robust distributed asynchronous Newton-Raphson



TODOs:

- 1 modify the initialization
- Modify the transmission / reception
- oppose the convergence properties

Robust distributed asynchronous Newton-Raphson

Initialization for quadratic programming

$$f_i(x) = \frac{1}{2} (a_i x - b_i)^2 \quad \Rightarrow \quad \begin{cases} y_i &\leftarrow a_i b_i \\ z_i &\leftarrow a_i^2 \end{cases}$$

Initialization for Newton-Raphson

 $f_i(x)$

$$\in \mathcal{C}^2, \quad f_i''(x) > c$$

$$\Rightarrow \quad \begin{cases} x_i & \leftarrow x^o \\ y_i = g_i^{\text{old}} = g_i & \leftarrow f_i''(x^o) x^o - f_i'(x^o) \\ z_i = h_i^{\text{old}} = h_i & \leftarrow f_i''(x^o) \end{cases}$$

Robust distributed asynchronous Newton-Raphson

Transmission for quadratic programming

$$\begin{array}{rcl} y_i & \leftarrow \frac{1}{|\mathcal{N}_i^{\text{out}}| + 1} y_i \\ z_i & \leftarrow \frac{1}{|\mathcal{N}_i^{\text{out}}| + 1} z_i \\ x_i & \leftarrow (1 - \varepsilon) x_i + \varepsilon \frac{y_i}{z_i} \end{array}$$

$$b_{i,y} \leftarrow b_{i,y} + y_i$$

 $b_{i,z} \leftarrow b_{i,z} + z_i$

Transmission for Newton-Raphson

$$\begin{array}{ll} y_i &\leftarrow \frac{1}{|\mathcal{N}_i^{\text{out}}| + 1} \begin{bmatrix} y_i + g_i - g_i^{\text{old}} \end{bmatrix} & \begin{array}{ll} b_{i,y} &\leftarrow b_{i,y} + y_i \\ b_{i,z} &\leftarrow b_{i,z} + z_i \end{bmatrix} \\ z_i &\leftarrow \frac{1}{|\mathcal{N}_i^{\text{out}}| + 1} \begin{bmatrix} z_i + h_i - h_i^{\text{old}} \end{bmatrix} & \begin{array}{ll} g_i^{\text{old}} &\leftarrow g_i \\ h_i^{\text{old}} &\leftarrow h_i \end{bmatrix} \\ x_i &\leftarrow (1 - \varepsilon) x_i + \varepsilon \frac{y_i}{[z_i]_c} & \begin{array}{ll} g_i &\leftarrow f_i''(x_i) x_i - f_i'(x_i) \end{bmatrix} \end{array}$$

Robust distributed asynchronous Newton-Raphson

Reception for quadratic programming

$$\begin{array}{ll} y_j & \leftarrow y_j + b_{i,y} - \beta_{i,y}^{(j)} \\ z_j & \leftarrow z_j + b_{i,z} - \beta_{i,z}^{(j)} \\ x_j & \leftarrow (1 - \varepsilon) x_j + \varepsilon \frac{y_j}{z_j} \end{array} \qquad \qquad \beta_{i,z}^{(j)} & \leftarrow b_{i,z} \end{array}$$

Reception for Newton-Raphson

o(i)

,

Convergence properties

Assumptions

- $f_i \in \mathcal{C}^2$, $f''_i(x) > c$
- fixed, strongly connected and directed network
- communications are persistent

(i.e., at least 1 communication in every $[t, t + \tau]$)

bounded packet losses

(i.e., number of consecutive failures is limited)

Proposition

$$\exists \ B_{\delta}\left(x^{*}\right)$$
 and $\varepsilon_{c} \in \mathbb{R}_{+}$ s.t. if $x^{o} \in B_{\delta}$ and $0 < \varepsilon < \varepsilon_{c}$ then

$$|x_i(k)-x^*| \leq c\lambda^k \qquad \forall i$$

for opportune $c \in \mathbb{R}_+$ and $\lambda < 1$

Numerical experiments

algorithms tuned with their best parameters and packet loss probability p = 0.1

$$f_i(\mathbf{x}) = \frac{(y_i - \langle \boldsymbol{\chi}_i, \widetilde{\mathbf{x}} \rangle)^2}{|y_i - \langle \boldsymbol{\chi}_i, \widetilde{\mathbf{x}} \rangle| + \beta} + \gamma \|\mathbf{x}\|_2^2$$





- \bullet tuning ε online
- partition-based updates of x
- equality constraints $A\mathbf{x} = \mathbf{b}$

Analysis of Newton-Raphson Consensus for multi-agent convex optimization under asynchronous and lossy communications

Ruggero CarliGiuseppe NotarstefanoLuca SchenatoDamiano Varagnolo

CDC 2015 - Osaka

December 14, 2015

damiano.varagnolo@ltu.se





licensed under the Creative Commons BY-NC-SA 2.5 European License: