

# Source Separation and Clustering of Phase-Locked Subspaces: Derivations and Proofs

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**Abstract**—Due to space limitations, our submission “Source Separation and Clustering of Phase-Locked Subspaces”, accepted for publication on the IEEE Transactions on Neural Networks in 2011, presented some results without proof. Those proofs are provided in this paper.

**Index Terms**—phase-locking, synchrony, source separation, clustering, subspaces

## APPENDIX A GRADIENT OF $|\varrho|^2$ IN RPA

In this section we derive that the gradient of  $|\varrho|^2$  is given by Eq. 6 of [1], where  $|\varrho|$  is defined as in Eq. 5 of [1]. Recall that  $\Delta\phi(t) = \phi(t) - \psi(t)$ , where  $\phi(t)$  is the phase of the estimated source  $y(t) = \mathbf{w}^T \mathbf{x}(t)$  and  $\psi(t)$  is the phase of the reference  $u(t)$ . Further, define  $\varrho \equiv |\varrho| e^{i\Phi}$ .

We begin by noting that  $|\varrho|^2 = (|\varrho| \cos(\Phi))^2 + (|\varrho| \sin(\Phi))^2$ , so that

$$\begin{aligned} \nabla |\varrho|^2 &= \nabla (|\varrho| \cos(\Phi))^2 + \nabla (|\varrho| \sin(\Phi))^2 \\ &= 2|\varrho| [\cos(\Phi) \nabla (|\varrho| \cos(\Phi)) + \sin(\Phi) \nabla (|\varrho| \sin(\Phi))]. \end{aligned}$$

Note that we have  $\frac{1}{T} \sum_{t=1}^T \cos(\Delta\phi(t)) = |\varrho| \cos(\Phi)$  and  $\frac{1}{T} \sum_{t=1}^T \sin(\Delta\phi(t)) = |\varrho| \sin(\Phi)$ , so we get

$$\begin{aligned} \nabla |\varrho|^2 &= 2|\varrho| \left\{ \cos(\Phi) \nabla \left[ \frac{1}{T} \sum_{t=1}^T \cos(\Delta\phi(t)) \right] + \right. \\ &\quad \left. + \sin(\Phi) \nabla \left[ \frac{1}{T} \sum_{t=1}^T \sin(\Delta\phi(t)) \right] \right\} \\ &= \frac{2|\varrho|}{T} \sum_{t=1}^T \left[ \sin(\Phi) \cos(\Delta\phi(t)) - \cos(\Phi) \sin(\Delta\phi(t)) \right] \times \\ &\quad \times \nabla \Delta\phi(t) \\ &= \frac{2|\varrho|}{T} \sum_{t=1}^T \sin[\Phi - \Delta\phi(t)] \nabla \Delta\phi(t). \end{aligned} \quad (1)$$

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Let’s now take a closer look on  $\nabla \Delta\phi(t)$ . Note that

$$\begin{aligned} \phi(t) &= \arctan \left( \frac{\mathbf{w}^T \mathbf{x}_h(t)}{\mathbf{w}^T \mathbf{x}(t)} \right) \quad \text{or} \\ \phi(t) &= \arctan \left( \frac{\mathbf{w}^T \mathbf{x}_h(t)}{\mathbf{w}^T \mathbf{x}(t)} \right) + \pi. \end{aligned}$$

Because of this we can say, if  $\mathbf{w}^T \mathbf{x}(t) \neq 0$ , that  $\nabla \phi(t) = \nabla \arctan \left( \frac{\mathbf{w}^T \mathbf{x}_h(t)}{\mathbf{w}^T \mathbf{x}(t)} \right)$ . On the other hand, since  $\Delta\phi(t) = \phi(t) - \psi(t)$  and  $\psi(t)$  does not depend on  $\mathbf{w}$ , we have (we will omit the time dependence for the sake of clarity):

$$\begin{aligned} \nabla \Delta\phi &= \nabla \phi - \nabla \psi = \nabla \phi = \nabla \arctan \left( \frac{\mathbf{w}^T \mathbf{x}_h}{\mathbf{w}^T \mathbf{x}} \right) \\ &= \frac{\mathbf{x}_h \cdot \mathbf{w}^T \mathbf{x} - \mathbf{x} \cdot \mathbf{w}^T \mathbf{x}_h}{\left[ 1 + \left( \frac{\mathbf{w}^T \mathbf{x}_h}{\mathbf{w}^T \mathbf{x}} \right)^2 \right] \cdot (\mathbf{w}^T \mathbf{x})^2} = \frac{\mathbf{I}_x(t) \cdot \mathbf{w}}{Y^2(t)}, \end{aligned}$$

where  $Y^2(t) = (\mathbf{w}^T \mathbf{x}(t))^2 + (\mathbf{w}^T \mathbf{x}_h(t))^2$  is the squared magnitude of the estimated source, and  $\mathbf{I}_x(t) = \mathbf{x}_h(t) \mathbf{x}^T(t) - \mathbf{x}(t) \mathbf{x}_h^T(t)$ , thus  $\mathbf{I}_{x_{ij}}(t) = X_i(t) X_j(t) \sin(\phi_i(t) - \phi_j(t))$ .

We can now replace  $\nabla \Delta\phi(t)$  in (1) to obtain

$$\begin{aligned} \nabla |\varrho|^2 &= \frac{2|\varrho|}{T} \left[ \sum_{t=1}^T \frac{\sin[\Phi - \Delta\phi(t)]}{Y^2(t)} \mathbf{I}_x(t) \right] \mathbf{w} \\ &= 2|\varrho| \left\langle \frac{\sin[\Phi - \Delta\phi(t)]}{Y^2(t)} \mathbf{I}_x(t) \right\rangle \mathbf{w}. \end{aligned} \quad (2)$$

## APPENDIX B GRADIENT OF $J_l$ IN IPA

In this section we show that the gradient of  $J_l$  in Eq. 7 of [1] is given by Eq. 8 of [1]. Throughout this whole section, we will omit the dependence on the subspace  $l$ , for the sake of clarity. In other words, we are assuming (with no loss of generality) that only one subspace was found. Whenever we write  $\mathbf{W}$ ,  $\mathbf{y}$ ,  $y_m$  or  $\mathbf{z}$ , we will be referring to  $\mathbf{W}_l$ ,  $\mathbf{y}_l$ ,  $(y_l)_m$  or  $\mathbf{z}_l$ .

The derivative of  $\log |\det \mathbf{W}|$  is  $\mathbf{W}^{-T}$ . We will therefore focus on the gradient of the first term of Eq. 7 of [1], which we will denote by  $P$ :

$$P \equiv \frac{1-\lambda}{N^2} \sum_{m,n} |\varrho_{mn}|^2.$$

Let’s rewrite  $P$  as  $P = \frac{1-\lambda}{N^2} \sum_{m,n} p_{mn}$  with  $p_{mn} = |\varrho_{mn}|^2$ . Define  $\Delta\phi_{mn} = \phi_m - \phi_n$ . Omitting the time dependency, we

have

$$\begin{aligned}
\nabla_{\mathbf{w}_j} p_{mn} &= 2|\varrho_{mn}| \nabla_{\mathbf{w}_j} \left| \langle e^{i\Delta\phi_{mn}} \rangle \right| \\
&= |\varrho_{mn}| \times \left( \langle \cos(\Delta\phi_{mn}) \rangle^2 + i \langle \sin(\Delta\phi_{mn}) \rangle^2 \right)^{-1/2} \times \\
&\quad \times \left[ 2 \langle \cos(\Delta\phi_{mn}) \rangle \nabla_{\mathbf{w}_j} \langle \cos(\Delta\phi_{mn}) \rangle + \right. \\
&\quad \left. + 2 \langle \sin(\Delta\phi_{mn}) \rangle \nabla_{\mathbf{w}_j} \langle \sin(\Delta\phi_{mn}) \rangle \right] \\
&= 2|\varrho_{mn}| \left| \langle e^{i\Delta\phi_{mn}} \rangle \right|^{-1} \times \\
&\quad \times \left[ - \langle \cos(\Delta\phi_{mn}) \rangle \langle \sin(\Delta\phi_{mn}) \nabla_{\mathbf{w}_j} \Delta\phi_{mn} \rangle + \right. \\
&\quad \left. + \langle \sin(\Delta\phi_{mn}) \rangle \langle \cos(\Delta\phi_{mn}) \nabla_{\mathbf{w}_j} \Delta\phi_{mn} \rangle \right], \quad (3)
\end{aligned}$$

where we have interchanged the partial derivative and the time average operators, and used

$$\left( \langle \cos(\Delta\phi_{mn}) \rangle^2 + i \langle \sin(\Delta\phi_{mn}) \rangle^2 \right)^{1/2} = \left| \langle e^{i\Delta\phi_{mn}} \rangle \right|.$$

Since  $\phi_m$  is the phase of the  $m$ -th measurement, its derivative with respect to any  $\mathbf{w}_j$  is zero unless  $m = j$  or  $n = j$ . In the former case, a reasoning similar to Appendix A shows that

$$\begin{aligned}
\nabla_{\mathbf{w}_j} \Delta\phi_{jk} &\equiv \nabla_{\mathbf{w}_j} \phi_j - \nabla_{\mathbf{w}_j} \phi_k = \nabla_{\mathbf{w}_j} \phi_j = \\
&= \frac{[\mathbf{z}_h \cdot \mathbf{z} - \mathbf{z} \cdot \mathbf{z}_h] \cdot \mathbf{w}_j}{Y_j^2} = \frac{\boldsymbol{\Gamma}_z \cdot \mathbf{w}_j}{Y_j^2}, \quad (4)
\end{aligned}$$

where  $\boldsymbol{\Gamma}_z(t) = \mathbf{z}_h(t)\mathbf{z}^\top(t) - \mathbf{z}(t)\mathbf{z}_h^\top(t)$ . It is easy to see that  $\nabla_{\mathbf{w}_j} \Delta\phi_{jk} = -\nabla_{\mathbf{w}_j} \Delta\phi_{kj}$ . Furthermore,  $p_{mm} = 1$  by definition, hence  $\nabla_{\mathbf{w}_j} p_{mm} = 0$  for all  $m$  and  $j$ . From these considerations, the only nonzero terms in the derivative of  $P$  are of the form

$$\begin{aligned}
\nabla_{\mathbf{w}_j} p_{jk} &= \nabla_{\mathbf{w}_j} p_{kj} = 2|\varrho_{jk}| \left| \langle e^{i(\phi_j - \phi_k)} \rangle \right|^{-1} \times \\
&\quad \times \left[ - \langle \cos(\Delta\phi_{jk}) \rangle \left\langle \sin(\Delta\phi_{jk}) \frac{\boldsymbol{\Gamma}_z \cdot \mathbf{w}_j}{Y_j^2} \right\rangle + \right. \\
&\quad \left. + \langle \sin(\Delta\phi_{jk}) \rangle \left\langle \cos(\Delta\phi_{jk}) \frac{\boldsymbol{\Gamma}_z \cdot \mathbf{w}_j}{Y_j^2} \right\rangle \right]. \quad (5)
\end{aligned}$$

We now define  $\Psi_{jk} \equiv \langle \phi_j - \phi_k \rangle = \langle \Delta\phi_{jk} \rangle$ . Plugging in this definition into Eq. (5) we obtain

$$\begin{aligned}
\nabla_{\mathbf{w}_j} p_{jk} &= 2|\varrho_{jk}| \times \\
&\quad \times \left[ - \cos(\Psi_{jk}) \left\langle \sin(\Delta\phi_{jk}) \frac{\boldsymbol{\Gamma}_z \cdot \mathbf{w}_j}{Y_j^2} \right\rangle + \right. \\
&\quad \left. + \sin(\Psi_{jk}) \left\langle \cos(\Delta\phi_{jk}) \frac{\boldsymbol{\Gamma}_z \cdot \mathbf{w}_j}{Y_j^2} \right\rangle \right] \\
&= 2|\varrho_{jk}| \left[ \left\langle - \cos \Psi_{jk} \sin \Delta\phi_{jk} \frac{\boldsymbol{\Gamma}_z \cdot \mathbf{w}_j}{Y_j^2} \right\rangle + \right. \\
&\quad \left. + \left\langle \sin \Psi_{jk} \cos \Delta\phi_{jk} \frac{\boldsymbol{\Gamma}_z \cdot \mathbf{w}_j}{Y_j^2} \right\rangle \right] \\
&= 2|\varrho_{jk}| \left\langle \sin(\Psi_{jk} - \Delta\phi_{jk}) \frac{\boldsymbol{\Gamma}_z \cdot \mathbf{w}_j}{Y_j^2} \right\rangle \cdot \mathbf{w}_j,
\end{aligned}$$

where we again used  $\sin(a - b) = \sin a \cos b - \cos a \sin b$  in the last step. Finally,

$$\begin{aligned}
\nabla_{\mathbf{w}_j} P &= \frac{1 - \lambda}{N^2} \sum_{m,n} \nabla_{\mathbf{w}_j} p_{mn} = 2 \frac{1 - \lambda}{N^2} \sum_{m < n} \nabla_{\mathbf{w}_j} p_{mn} = \\
&= 4 \frac{1 - \lambda}{N^2} \sum_{k=1}^N |\varrho_{jk}| \left\langle \sin[\Psi_{jk} - \Delta\phi_{jk}(t)] \frac{\boldsymbol{\Gamma}_z(t)}{Y_j(t)^2} \right\rangle \cdot \mathbf{w}_j.
\end{aligned}$$

which is Eq. 8 of [1].

## APPENDIX C GRADIENT OF $J$ IN PSCA

In this section we derive Eq. 10 of [1] for the gradient of  $J$ . Recall that  $J$  is given by

$$J \equiv \sum_{j=1}^P \left| \sum_{i=1}^N u_{ij} \right| = \sum_{j=1}^P \left| \sum_{i=1}^N \sum_{k=1}^P v_{ik} w_{kj} \right|$$

where the  $w_{kj}$  are real coefficients that we want to optimize and the  $v_{ik}$  are fixed complex numbers. Also recall that  $\text{Re}(\cdot)$  and  $\text{Im}(\cdot)$  denote the real and imaginary parts.

We begin by expanding the complex absolute value:

$$\begin{aligned}
\sum_j \left| \sum_{i,k} v_{ik} w_{kj} \right| &= \sum_j \left\{ \left[ \text{Re} \left( \sum_{i,k} v_{ik} w_{kj} \right) \right]^2 \right. \\
&\quad \left. + \left[ \text{Im} \left( \sum_{i,k} v_{ik} w_{kj} \right) \right]^2 \right\}^{1/2}.
\end{aligned}$$

When computing the derivative in order to  $w_{kj}$ , only one term in the leftmost sum matters. Thus,

$$\begin{aligned}
\frac{\partial J}{\partial w_{kj}} &= \\
&= 2 \left( \left[ \text{Re} \left( \sum_{i,k} v_{ik} w_{kj} \right) \right]^2 + \left[ \text{Im} \left( \sum_{i,k} v_{ik} w_{kj} \right) \right]^2 \right)^{-1/2} \times \\
&\quad \times \left[ \frac{\partial \left[ \text{Re} \left( \sum_{i,k} v_{ik} w_{kj} \right) \right]^2}{\partial w_{kj}} + \frac{\partial \left[ \text{Im} \left( \sum_{i,k} v_{ik} w_{kj} \right) \right]^2}{\partial w_{kj}} \right] \\
&= \frac{1}{\left| \sum_i u_{ij} \right|} \left[ \text{Re} \left( \sum_{i,k} v_{ik} w_{kj} \right) \frac{\partial \text{Re} \left( \sum_{i,k} v_{ik} w_{kj} \right)}{\partial w_{kj}} + \right. \\
&\quad \left. + \text{Im} \left( \sum_{i,k} v_{ik} w_{kj} \right) \frac{\partial \text{Im} \left( \sum_{i,k} v_{ik} w_{kj} \right)}{\partial w_{kj}} \right]. \quad (6)
\end{aligned}$$

In the sums inside the derivatives, the sum on  $k$  can be dropped as only one of those terms will be nonzero. Therefore,

$$\begin{aligned}
\frac{\partial \text{Re} \left( \sum_{i,k} v_{ik} w_{kj} \right)}{\partial w_{kj}} &= \frac{\partial \text{Re} \left( \sum_i v_{ik} w_{kj} \right)}{\partial w_{kj}} \\
&= \frac{\partial \text{Re} \left( \sum_i v_{ik} \right) w_{kj}}{\partial w_{kj}} = \text{Re} \left( \sum_i v_{ik} \right) = \text{Re}(\bar{v}_k),
\end{aligned}$$

where we used  $\bar{v}_i \equiv \sum_k v_{ki}$  to denote the sum of the  $i$ -th column of  $\mathbf{V}$ . Similarly,

$$\frac{\partial \operatorname{Im}\left(\sum_{i,k} v_{ik} w_{kj}\right)}{\partial w_{kj}} = \operatorname{Im}(\bar{v}_k).$$

These results, with the notation  $\bar{u}_j \equiv \sum_k v_{jk}$  as the sum of the  $j$ -th column of  $\mathbf{U}$ , can be plugged into Eq. (6) to yield

$$\mathbf{G}_{kj} = \frac{\partial J}{\partial w_{kj}} = \frac{1}{|\bar{u}_j|} \left[ \operatorname{Re}(\bar{v}_k) \times \operatorname{Re}(\bar{u}_j) + \operatorname{Im}(\bar{v}_k) \times \operatorname{Im}(\bar{u}_j) \right].$$

#### APPENDIX D MEAN FIELD

In this section we derive Eq. 9 of [1] for the interaction of an oscillator with the cluster it is part of. We will assume that there are  $N_j$  oscillators in this cluster, coupled all-to-all with the same coupling coefficient  $\kappa$ , and that all inter-cluster interactions are weak enough to be disregarded. We begin with Kuramoto's model (Eq. 1 of [1]) omitting the time dependency:

$$\begin{aligned} \dot{\phi}_i &= \omega_i + \sum_{k \in c_j} \kappa_{ik} \sin(\phi_k - \phi_i) + \sum_{k \notin c_j} \kappa_{ik} \sin(\phi_k - \phi_i) \\ \dot{\phi}_i &= \omega_i + \sum_{k \in c_j} \kappa_{ik} \sin(\phi_k - \phi_i) \\ &= \omega_i + \sum_{k \in c_j} \kappa_{ik} \frac{e^{i(\phi_j - \phi_i)} - e^{-i(\phi_j - \phi_i)}}{2i} \\ &= \omega_i + \frac{e^{-i\phi_i}}{2i} \sum_{k \in c_j} \kappa_{ik} e^{i\phi_k} - \frac{e^{i\phi_i}}{2i} \sum_{k \in c_j} \kappa_{ik} e^{-i\phi_k}. \end{aligned}$$

We now plug in the definition of mean field  $\varrho_{c_j} e^{i\Phi_{c_j}} = \frac{1}{N_j} \sum_{k \in c_j} e^{i\phi_k}$  to obtain

$$\begin{aligned} \dot{\phi}_i &= \omega_i + N_j \frac{e^{-i\phi_i}}{2i} \kappa \varrho_{c_j} e^{i\Phi_{c_j}} - N_j \frac{e^{i\phi_i}}{2i} \kappa \varrho_{c_j} e^{-i\Phi_{c_j}} \\ &= \omega_i + N_j \kappa \varrho_{c_j} [\sin(\Phi_{c_j} - \phi_i) - \sin(\phi_i - \Phi_{c_j})] \\ &= \omega_i + 2N_j \kappa \varrho_{c_j} \sin(\Phi_{c_j} - \phi_i). \end{aligned}$$

#### REFERENCES

- [1] M. Almeida, J.-H. Schleimer, J. Bioucas-Dias, and R. Vigário, "Source separation and clustering of phase-locked subspaces," *IEEE Transactions on Neural Networks* (accepted), 2011.