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Proposal of higher-order tensor independent component analysis for signal separation in multiple-input multiple-output respiration/heartbeat remote sensing*

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***Abstract*— This paper proposes higher-order tensor independent component analysis (HOT-ICA). HOT-ICA is a tensor ICA that makes effective use of the relationships among the axes of a separating tensor. We deal with multiple-target signal separation in a multiple-input multiple-output (MIMO) radar system to detect respiration and heartbeat. Numerical physical experiments demonstrate the significance of the HOT-ICA which keeps the tensor structure unchanged to fully utilizes the high-dimensionality of the separation tensor.**

I. INTRODUCTION

Conventional heartbeat sensing systems use contact-type electrodes put on a human body. Recent vital sign detectors sometimes employ non-contact methods. Among them, there have been a lot of research on respiration and heartbeat measurement based on Doppler radar. For example, some studies included rubble by assuming measurement in disasters [1], [2], [3], [4], [5], [6].

It is necessary to separate the target signal from other targets and noise for measurement in an environment including obstacles and multiple targets. In this case, independent component analysis (ICA) is effective. The purpose of ICA is to remove noise and/or separate targets by finding a separation matrix for linearly transforming mixed signals to original signals based on the signals' statistical properties. Ref. [7] describes the mathematical analysis and many algorithms studied in the past.

The pair of in-phase and orthogonal components are essentially a single complex signal to be treated in the framework of complex-valued neural network [8], [9], [10]. This paper also deals with complex signals as an entity. The measurement environment, in addition, changes depending on target movement and obstacles existence. We thus aim to adaptively process the properties of complex signals in time-sequential observation. For example, Refs. [11] and [12] managed new data every time a data is fed. The scheme is called online ICA.

Signal processing with MIMO measurement leads to constructing multi-axis data tensor having signal path information. Then multilinear ICA (MICA) was proposed [13], [14] that incorporates higher-order tensors into the ICA processing. MICA often uses the tensor decomposition proposed by Tucker [15]. It is true that MICA works for separation[16], [17], [18], [19], [20], [21], [22], [23]. However, it is expected to realize more meaningful tensor ICA processing in such a manner that the relationship among axes remain nondestructed.

This paper proposes higher-order tensor independent component analysis (HOT-ICA). We take up a MIMO Doppler radar to show the strength of HOT-ICA processing. Experiments elucidate dynamics advantageous in HOT-ICA to manipulate the contribution of respective components in the separation tensor, according to the path information of respective elements, in its independence evaluation.

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II. PHYSICAL AND MATHEMATICAL BACKGROUND

A. Doppler radar

Fig. 1 shows the measurement scene in an environment without obstacles. The microwave is radiated from one of the transmitting antennas Tx and propagates to the targets. After backscattering on the body surface, it is observed by the receiving antennas Rx.

Assuming the microwave with a frequency of f_t, the phase $\Phi(t)$ of the received radio wave is expressed as a function of the target displacement $x(t)$ as

$$\Phi(t) = 2\pi f_t t + \frac{4\pi x(t)}{\lambda} + \phi_0 \tag{1}$$

where λ and ϕ_0 represent the wavelength and the phase offset, respectively.

The complex amplitude can be calculated from the in-phase component $I(t)$ and the quadrature component $Q(t)$ obtained by orthogonal detection circuit. By ignoring the phase offset, we can write the received signal as

$$\begin{aligned} A(t)\cos\left[\frac{4\pi x(t)}{\lambda}\right] + jA(t)\sin\left[\frac{4\pi x(t)}{\lambda}\right] \\ \equiv I(t) + jQ(t) \equiv A(t)\exp\left[j\frac{4\pi x(t)}{\lambda}\right]. \end{aligned} \tag{2}$$

Typically, human respiration causes displacement of about $1\ \mathrm{cm}$ to be detected as the phase change shown in (1).

B. Conventional online CF-ICA

Online complex-valued frequency-domain ICA (CF-ICA) is an online processing ICA that handles complex signals in

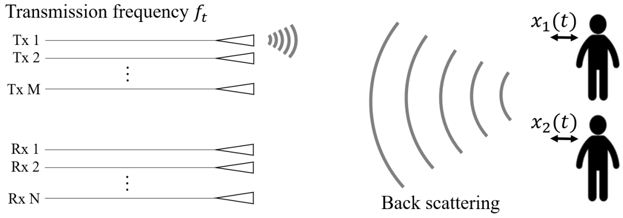

Fig. 1. Measurement in Doppler radar.

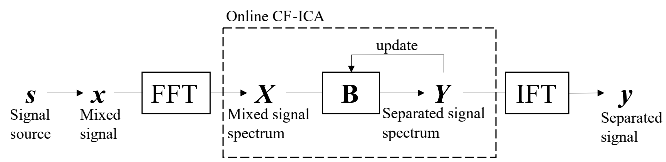

Fig. 2. Flow of online CF-ICA.

the frequency domain [6]. The flow of the process is shown in Fig. 2. In general, online ICA learns the separation matrix $\mathbf{B}$ for time-series signals that are fed one after another:

$$\mathbf{B} \longleftarrow \mathbf{B} + \Delta\mathbf{B}. \tag{3}$$

Online CF-ICA's online algorithm is based on equivariant adaptive separation via independence (EASI) [12]. EASI is a method to simultaneously execute the two processes in ICA, namely, whitening and independence maximization, expressed by a single update formula. The online CF-ICA is an extension of this operation to the frequency domain. The frequency-domain processing has an advantage that it is easy to narrow down the frequency band of the signals used in the learning between $f_{\min}$ and $f_{\max}$.

The separation matrix $\mathbf{B}$ is assumed to perform the whitening and independence maximization in series [6]. Combining the updating fractions of whitening and independence maximization derives the learning rule of the separation matrix $\mathbf{B}$. In the instantaneous mixing case, the linearity of the short-time Fourier transform (STFT) results in the applicability of the time-domain ICA to the frequency domain. Thus, the following separation learning is possible for discrete time t_d and angular frequency $\omega \quad (2\pi f_{\min} < \omega < 2\pi f_{\max})$:

$$\boldsymbol{Y}(\omega, t_d) = \mathbf{B}(t_d)\boldsymbol{X}(\omega, t_d), \tag{4}$$

$$\Delta\mathbf{B} = -\mu[\boldsymbol{Y}\boldsymbol{Y}^{\mathrm{H}} - \mathbf{I} + g(\boldsymbol{Y})\boldsymbol{Y}^{\mathrm{H}} - \boldsymbol{Y}g(\boldsymbol{Y})^{\mathrm{H}}]\mathbf{B}. \tag{5}$$

where μ is the learning rate, $\mathbf{I}$ is the identity matrix, $g(\cdot)$ is a nonlinear function, and the complex EASI is obtained by changing transposition $[\cdot]^{\mathrm{T}}$ to the transpose conjugate $[\cdot]^{\mathrm{H}}$.

III. PROPOSAL OF HIGHER-ORDER TENSOR INDEPENDENT COMPONENT ANALYSIS (HOT-ICA)

We propose HOT-ICA as a new ICA method. HOT-ICA is a method effective in particular in a measurement system based on MIMO. The data tensor type dealt with in HOT-ICA is shown in Fig. 3(b) compared to that of ICA (Fig. 3(a)).

Let the number of transmitting antennas be p_t, the number of receiving antennas be p_r, and the obtained mixed signals

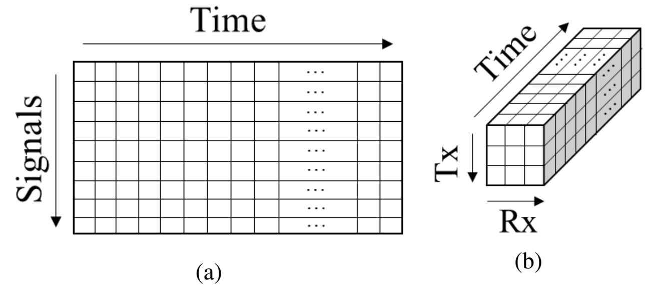

Fig. 3. Shapes of received data tensor : (a) CF-ICA (b) HOT-ICA.

be $\mathbf{x}(t) \equiv x(t)^{(\gamma,\delta)} \in \mathbb{C}^{p_t \times p_r}$. We find the equation that transforms the mixed signals into statistically independent signals $\mathbf{y}(t) \equiv y(t)^{(\alpha,\beta)} \in \mathbb{C}^{p_t \times p_r}$. By referring to (4), we adopt $\underline{\underline{\mathbf{B}}} \equiv B^{(\alpha,\beta,\gamma,\delta)} \in \mathbb{C}^{p_t \times p_r \times p_t \times p_r}$ for the transformation expressed as

$$Y(\omega, t_d)^{(\alpha,\beta)} = \sum_{\gamma=1}^{p_t}\sum_{\delta=1}^{p_r} B(t_d)^{(\alpha,\beta,\gamma,\delta)} X(\omega, t_d)^{(\gamma,\delta)} \tag{6}$$

We extend the update formula (5) to HOT-ICA calculation to construct the following new update formula, that is,

$$\Delta B^{(\alpha,\beta,\gamma,\delta)} = \sum_{\varepsilon=1}^{p_t}\sum_{\zeta=1}^{p_r} W^{(\alpha,\beta,\varepsilon,\zeta)}\, B^{(\varepsilon,\zeta,\gamma,\delta)} \tag{7}$$

where we define learning weight $\underline{\underline{\mathbf{W}}} \equiv W^{(\alpha,\beta,\gamma,\delta)} \in \mathbb{C}^{p_t \times p_r \times p_t \times p_r}$ with conjugate of $Y \quad (\equiv \bar{Y})$ as

$$\begin{aligned} W^{(\alpha,\beta,\gamma,\delta)} \quad &= \quad -\mu \Big[Y^{(\alpha,\beta)} \bar{Y}^{(\gamma,\delta)} + g(Y^{(\alpha,\beta)}) \bar{Y}^{(\gamma,\delta)} \\ &\quad + Y^{(\alpha,\beta)} g(\bar{Y})^{(\gamma,\delta)} - I^{(\alpha,\beta,\gamma,\delta)} \Big] \end{aligned} \tag{8}$$

where $\underline{\underline{\mathbf{I}}} \in \mathbb{C}^{p_t \times p_r \times p_t \times p_r}$ is

$$I^{(\alpha,\beta,\gamma,\delta)} = \begin{cases} 1 & (\alpha = \gamma \cap \beta = \delta), \\ 0 & (\alpha \neq \gamma \cup \beta \neq \delta). \end{cases} \tag{9}$$

When we use a MIMO system, it is inevitable that respective antennas have various conditions and/or situations different from one another depending on the environment. For example, an antenna may be relatively noisy or defective. In such a case, we should improve the robustness of the overall learning. This can be achieved by reducing the learning weight associated with the antenna. To make it possible, we break down the update formula (7). By assuming that the update tensor components related to the transmitting antennas $\mathrm{Tx1}, \mathrm{Tx2}, \ldots, \mathrm{Tx}M$ are $\Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Tx1}}, \Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Tx2}}, \ldots, \Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Tx}M}$ and that those related to the receiving antennas $\mathrm{Rx1}, \mathrm{Rx2}, \ldots, \mathrm{Rx}N$ are $\Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Rx1}}, \Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Rx2}}, \ldots, \Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Rx}N}$, we can express $\Delta\underline{\underline{\mathbf{B}}}$ as

$$\begin{aligned} \Delta\underline{\underline{\mathbf{B}}} \quad &= \quad \frac{1}{2}\Big(\Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Tx1}} + \Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Tx2}} + \cdots + \Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Tx}M} \\ &\quad + \Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Rx1}} + \Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Rx2}} + \cdots + \Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Rx}N} \Big) \end{aligned} \tag{10}$$

where $\Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Tx}m}, \Delta\underline{\underline{\mathbf{B}}}_{\mathrm{Rx}n} \quad (1 \leq m \leq M)$ and $(1 \leq n \leq N)$

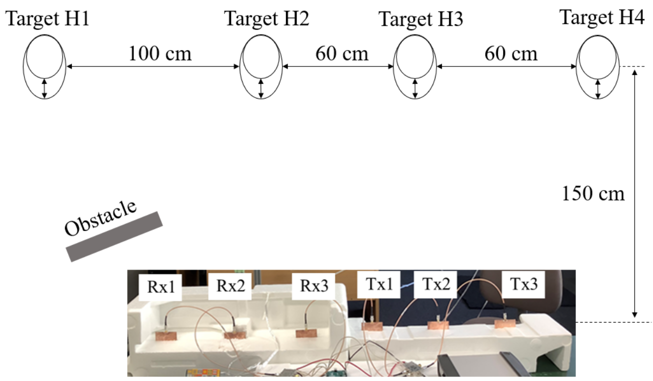

Fig. 4. Placement of antennas, targets and an obstacle.

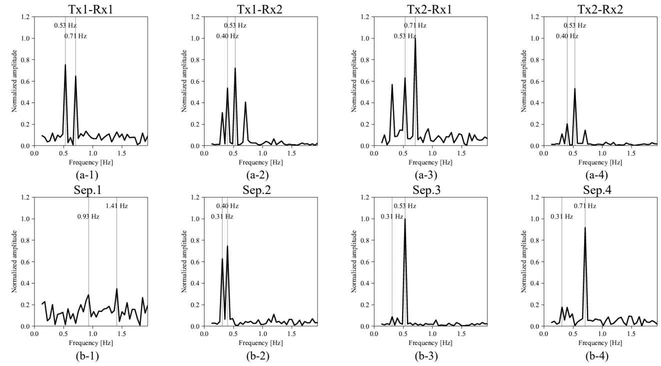

Fig. 5. Spectra of (a-⋆) mixed signals and (b-⋆) separated signals using CF-ICA in the last time window.

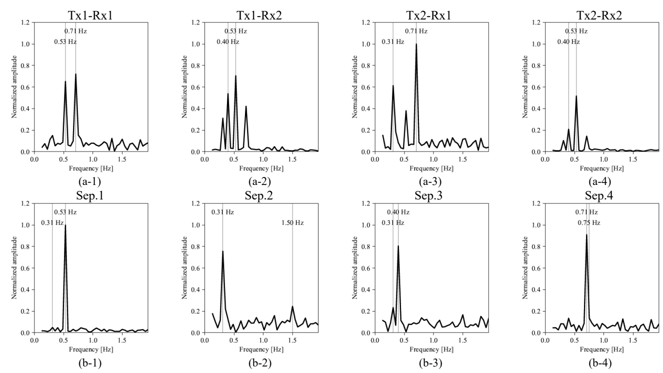

Fig. 6. Spectra of (a-⋆) mixed signals and (b-⋆) separated signals using HOT-ICA with weighting $\eta_{\mathrm{Rx1}} = 0$ in the last time window.

are defined as

$$\Delta B_{\mathrm{Tx}m}^{(\alpha,\beta,\gamma,\delta)} = \sum_{\varepsilon=1}^{p_t} \sum_{\zeta=1}^{p_r} W_{\mathrm{Tx}m}^{(\alpha,\beta,\varepsilon,\zeta)} \, B^{(\varepsilon,\zeta,\gamma,\delta)}, \tag{11}$$

$$\Delta B_{\mathrm{Rx}n}^{(\alpha,\beta,\gamma,\delta)} = \sum_{\varepsilon=1}^{p_t} \sum_{\zeta=1}^{p_r} W_{\mathrm{Rx}n}^{(\alpha,\beta,\varepsilon,\zeta)} \, B^{(\varepsilon,\zeta,\gamma,\delta)}. \tag{12}$$

The learning weight tensors $\underline{\underline{\mathbf{W}}}_{\mathrm{Tx}m}$ and $\underline{\underline{\mathbf{W}}}_{\mathrm{Rx}n}$ are represented as

$$W_{\mathrm{Tx}m}^{(\alpha,\beta,\gamma,\delta)} = \begin{cases} W^{(\alpha,\beta,\gamma,\delta)} & (\gamma = m), \\ 0 & (\gamma \neq m), \end{cases} \tag{13}$$

$$W_{\mathrm{Rx}n}^{(\alpha,\beta,\gamma,\delta)} = \begin{cases} W^{(\alpha,\beta,\gamma,\delta)} & (\delta = n), \\ 0 & (\delta \neq n). \end{cases} \tag{14}$$

For example, a coefficient η_{Rx1} $(0 \leqq \eta_{\mathrm{Rx1}} < 1)$ can individually reduce the weight component $\underline{\underline{\mathbf{W}}}_{\mathrm{Rx1}}$ in the learning weight tensor for defective antenna Rx1 to obtain a new tensor component

$$\underline{\underline{\mathbf{W}}}'_{\mathrm{Rx1}} = \eta_{\mathrm{Rx1}} \underline{\underline{\mathbf{W}}}_{\mathrm{Rx1}} \tag{15}$$

to realize a higher robustness.

Note that tensor calculation of HOT-ICA is different from that of MICA based on the Tucker decomposition, which requires matricization. HOT-ICA maintains the mutual relationship among the axes without breaking the original tensor's structure. Hence, HOT-ICA can perform adaptive signal-source separation every time the receiving antennas acquire data including possible changes in the measurement environment, resulting in the increase of robustness.

IV. NUMERICAL EXPERIMENT

A. Settings of numerical physical experiment

We conduct a numerical experiment assuming a continuous wave (CW) MIMO Doppler radar front-end (see Section II-A), and a signal-source separation based on the HOT-ICA to process mixed signals. The signals include not only the original signals from the targets but also various noise. The number of transmitting antennas Tx and the number of receiving antennas Rx are 2 respectively, and the number of targets (humans: H) is set to 4. We performed numerical experiments by assigning the amplitude and frequency of the respiration and heartbeat signals to each of the targets H1–H4. Fig. 4 shows the placement of the antennas and targets. An obstacle is placed between Target H1 and Receiving antenna Rx1.

The obstacle has two effects on the mixed signals. The first is that the obstacle gives an attenuation to the original signal from Target H1 obtained by Receiving antenna Rx1. The second is that the signal received by Receiving antenna Rx1 includes large noise compared to the noise at other receiving antennas. This implies a situation where something is wrong with a particular receiving antenna.

B. Conventional online CF-ICA

Fig. 5 shows the results of online CF-ICA processing where the obstacle affects the received signals. The top graphs in Fig. 5 show the received signal spectra $\mathbf{X}(\omega, T_d)$ at the last STFT time window obtained by microwave transmitted by Tx1 and received by Rx1, denoted as (Tx1, Rx1) as well as, (Tx1, Rx2), (Tx2, Rx1), and (Tx2, Rx2) in the order from left to right. Large noise coming via Receiving antenna Rx1 appears in the mixed signal spectra (see Figs. 5 (a-1) and (a-3)). In the processed signals shown in Fig. 5 (b-2), the respiration frequencies of Targets H1 and H2 appear in the spectrum. That is, they are not separated well. In the meanwhile in Fig. 5 (b-1), noise is dominant. We found that, when there is an obstacle, the separation learning using online CF-ICA becomes unstable.

C. HOT-ICA with weighting

Fig. 6 shows the results of the HOT-ICA with weights in relation to Receiving antenna Rx1 in the same environment. Specifically, represented in formula (15), we take $\eta_{\mathrm{Rx1}} = 0$. Such sudden reduction of mixed signals and/or the increase of noise are detectable in the front-end so that the weighting coefficient can be obtained automatically. Compared with Fig. 5 (b-$\star$), each spectrum of the separated signals in Fig. 6 (b-$\star$) has a specific signal peak. Individual target signals are distributed to respective spectra separately. Thus, we have found the effectiveness of HOT-ICA with the weighting related to obstacles in the propagation paths and/or defects in the front-end.

HOT-ICA can perform the weighting to respective components of the weight tensor $\underline{\underline{\mathbf{W}}}$ (fourth-order tensor). That is, it realizes direct control the parameters in the learning dynamics. This successful weighting effect reveals the significance of keeping the tensor structure unchanged by getting free from Tucker decomposition.

V. CONCLUSION

This paper proposed HOT-ICA. It is a new signal-separation method suitable for the measurement data of human respiration and heartbeat employing a CW MIMO Doppler radar. In the environment for the numerical experiment, we set an obstacle and a malfunction of an antenna in the environment for the numerical experiment to demonstrate the effectiveness of HOT-ICA with weighting. As a result, we found that HOT-ICA with weighting is more robust than conventional method in signal-source separation learning, which leads to more flexible measurement in various situations. This was achieved by HOT-ICA's signal processing dynamics that utilizes the nature of high-dimensional tensor structure.

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