Hybrid ICA/Classical Adaptive Beamforming for Self-Organizing Collaborative Wireless Networks

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Abstract

Adaptive beamforming is essential for maximizing the utilization of valuable wireless communication spectrum resources by enabling spatial multiplexing of signals, frequency reuse, and rejection of interference. Yet it is not used in many important applications involving ad hoc networks of wireless nodes due to physical, algorithmic, and cost issues which include the power, space, and hardware needed for a fixed antenna array on each node, precise array calibration requirements, fast changes in signal propagation and angle of arrival due to node mobility, synchronization of long training signals, long convergence times, and algorithm complexity. We describe a hybrid approach to adaptive beamforming which addresses these issues by combining the flexibility of blind source separation based on ICA with the performance of classical non-blind maximum SINR adaptive beamforming. These techniques can be used for collaborative beamforming in which multiple nodes share antenna, spatial diversity, and battery resources.

1. Introduction

Ad hoc networks of spatially distributed and possibly mobile wireless nodes have many potential applications in reconnaissance, target identification, and communications. An example is the ad hoc spatially distributed sensor networks envisioned by the Darpa SensIT program. Several challenges must be met in order for such systems to be practical and fieldable. Efficient utilization of battery power is essential. Development of algorithms for self-organization of the ad hoc network into a topology optimized for the application is also important. Locally-oriented self-organization, driven by spatial locality and resource utilization metrics, can be used to form virtual clusters of wireless nodes. Self-organization can drive formation of flexible ad hoc networks which adapt to changing situations, such as nodes dropping out or changing environmental conditions. These virtual clusters can be formed for purposes of parallel computation, sharing of resources, and forming phased sensor arrays for improved detection. The emergent sensor clusters become the computational units of the sensor network.

2. Virtual Antenna Arrays

In order to accomplish mission goals, the sensor clusters must communicate with other clusters and with a basestation. Techniques must be developed for communication methods which utilize battery power efficiently. If the nodes are self-organized into clusters, communication efficiency can be maximized by allowing members of a cluster to collaborate in sending and receiving messages. The nodes within a cluster can collaborate in terms of detecting and processing sensor data. The processed information must then be transmitted back to a basestation or to another cluster. If the cluster could combine the battery power and antenna diversity of individual sensors in a coherent fashion, then the available resources would be fully utilized, resulting in maximum efficiency. The sensor clusters should communicate using collaborative beamforming in which a *virtual* adaptive antenna array is formed from antennas on the individual nodes in a cluster. (Fig. 1.) Training signals can be used to adapt the antenna weights if the training can be done on time scales short compared to the dephasing time for local oscillators in a cluster. By forming such virtual antenna arrays, the spatial diversity of the nodes can be used to provide antenna gain in the direction of the desired receiver/transmitter while simultaneously nulling out interference and reducing noise. In addition, battery resources within a cluster can be pooled for communication. The resultant improved antenna performance will reduce the need for multiple hops, thereby reducing traffic on the network and further conserving battery resources. In addition, it will allow communication with the basestation at farther stand-off distances. In this paper we describe an approach for forming virtual antenna arrays from the randomly distributed nodes in a cluster and performing adaptive beamforming using short training signals.

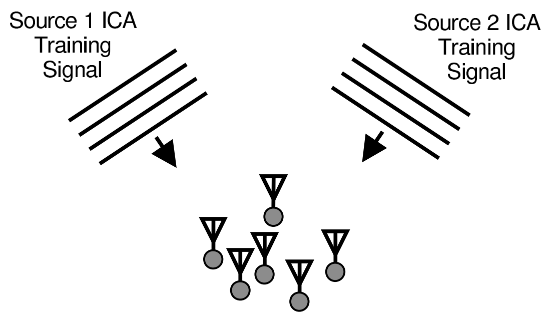

Fig. 1. Antenna gain, spatial diversity, and battery power of multiple randomly distributed wireless nodes can be pooled by forming a virtual antenna array, thereby increasing the datalink bandwidth.

3. Reference-Based ICA Beamforming

A virtual antenna array cannot be formed in an ad hoc cluster using classical beamsteering techniques because the wireless nodes will be distributed randomly and unpredictably, resulting in a completely uncalibrated array. It will not be possible to formulate steering vectors *a priori*. Therefore, a classical minmum variance distortionless response beamformer cannot be formed. However, if the cluster is attempting to communicate with other cooperative clusters or a basestation, then pilot or training signals can be used to adapt the virtual array. Adaptive beamforming training methods used in other contexts will have problems in this application. LMS adaptation, for example, requires a training signal to be stored at each node in order to form an error signal representing the difference between the local and received training signals.[1] This brings up issues of synchronization. LMS is an iterative training method which can be slow and unpredictable in its convergence rate, depending on the spread of eigenvalues of the noise covariance matrix. In addition, it tends to select the strongest signal and rejects the others, which can be a problem if a weak signal needs to be received. Finally, it is suboptimal in terms of SINR performance.

Ideally, the virtual beamforming should not require synchronization of the training signal with stored references in the sensors, should not require array calibration or knowledge of the signal angle of arrival, should adapt quickly and predictably, allow communication with multiple nodes simultaneously, and provide good rejection of jammers and noise. Previously proposed beamformers cannot meet all these requirements simultaneously. In this paper we describe adaptive beamforming methods based on ICA (Independent Component Analysis)[2] which meet these requirements.

ICA is a family of techniques being actively researched worldwide for Blind Source Separation (BSS) in which the original signals are extracted from mixtures of the signals without using prior knowledge of the signals.[3] ICA separates signals on the basis of the statistical independence of the signals. Since mixtures of signals are not independent, transforms based on higher-order statistical moments such as the kurtosis of the signal pdf can be used to maximize independence and thereby separate the signals. A variety of ICA algorithms have been published recently based on neural networks, natural gradients, diagonalization of cumulant matrices, etc. Many applications of ICA have been demonstrated, including signal processing for antenna arrays, which generate complex-valued linear mixtures of signals. ICA can be used to extract signals and effectively implement beamforming without prior knowledge of the signals or calibration of the antenna array.

In our simulations of ICA-based beamforming we assumed the general multi-path signal mixture model shown in Fig. 2 in which the m-th antenna element mixture is given by

$$y_m(t) = \sum_k \sum_p a_{mkp} \int b_{mkp}(\tau) s_k\left(t - \tau - \tau_{kp}\right) d\tau + n_m(t) \tag{1}$$

where

$$a_{mkp} = \exp\left(j\phi_{kp}\right) \exp\left(j2\pi d_m \sin\theta_{kp} / \lambda\right) \tag{2}$$

is the received amplitude at node m for source k and signal path p, assuming the node antenna is located at position d_m. θ_{kp} is the angle of arrival (AOA) for source k traveling along path p, ϕ_{kp} is a random phase factor, and λ is the rf wavelength. τ_{kp} represents the multipath delay for source k and path p. Channel delay spreading effects are represented by the channel filter impulse responses $b_{mkp}(t)$ which are assumed different for each signal/path/antenna combination. In our simulations we assumed unity amplitude and random phases for the channel filter coefficients. Finally, we add gaussian noise n_m to each signal mixture.

Typically, ICA is used for BSS where the signals to be separated are unknown beforehand. However, in the ad hoc wireless network application we can take advantage of the fact that communication is to be performed between cooperative nodes by using a pilot or reference signal which is known *a priori* and is optimized for fast ICA separation using a small number of samples. The target node or basestation periodically transmits the short pilot signal to probe the communication channel. If ICA can be performed fast enough, then the beamforming weights can be calculated on a time scale that is short relative to how fast the channel conditions are changing and also relative to the dephasing time between the individual sensor local oscillators. (The dephasing time can be increased using synchronization signals shared within the cluster.) Data packets can then be transmitted or received until conditions change sufficiently to require retraining of the virtual array. The advantages over LMS training include: no error signal is calculated, synchronization between a stored and received reference is not required, convergence can be fast, and beamforming can be performed for multiple signals simultaneously. This fast reference-based ICA (r-ICA) beamforming can also be used to compensate for a limited amount of relative motion between the sensor nodes.

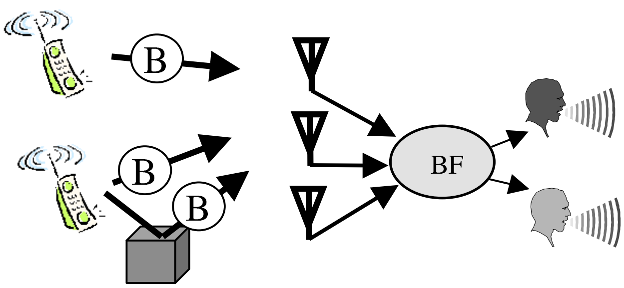

Fig.2. Simulation model for adaptive beamforming includes multiple propagation paths for each source signal with associated unique channel filters B. Each source signal is delayed multiple times due to both the channel filter and the multiple path delays, multiplied by both random and antenna phase shifts, and summed with other signals and receiver noise to form the mixture inputs to the adaptive beamforming algorithm BF which separates the signals.

Simulation results for r-ICA are shown in Fig. 3 for the case of non-convolutive mixtures and only a single path for each of two signals. The antenna array consists of two nodes forming a two element array. The first signal is a reference or pilot waveform which is used to probe the channel and adapt the ICA beamformer before data is sent. The pilot signal is designed to be locally stationary and have a kurtosis value much different from the expected typical range of kurtosis values of speech and other man-made signals. In our experiments we used a sinusoidal signal passed through a point nonlinearity. The second signal was a bandpass AM carrier-suppressed signal modulated by speech sampled at 8 Khz. The pilot signal and speech signal AOAs were -15^{o} and 45^{o}, respectively. By tailoring the pilot signal for good ICA performance, source separation is maximized and a smaller number of time samples can be used. In the two-node r-ICA simulation of Fig. 3, good separation of the signals was obtained using only 125 time samples. The ICA output SINRs were 51 db and 21db for the speech and pilot signals, respectively. The initial SINRs were 6 db and -6 db using untrained antenna weights equal to unity. Such a small training set allows rapid adaptation to changing environmental conditions, including changes in the geometry of the antenna array.

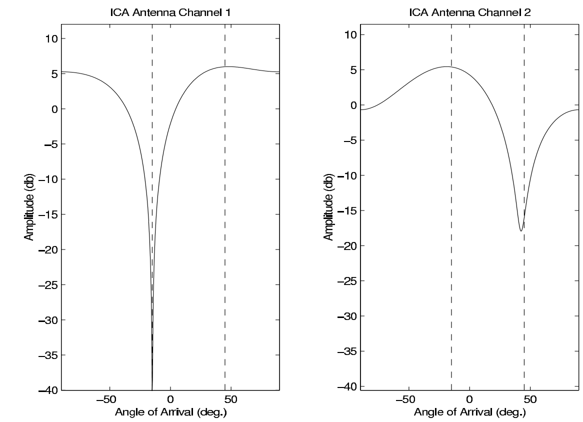

Fig. 3. Adaptive antenna array angular responses for the r-ICA 2-element beamforming simulation. The pilot signal and speech signal AOAs were -15^{o} and 45^{o}, respectively. The pilot signal was designed for ICA separation using a small number of samples. Only 125 time samples were used to obtain output SINRs of 51 db and 21 db for the speech and pilot signals, respectively. The initial SINRs were 6 db and -6 db using untrained antenna weights equal to unity.

4. Hybrid ICA-MVDR Beamforming

Time Domain ICA-MVDR

Although beamforming using r-ICA performs well, it is not guaranteed to achieve optimal performance in terms of SINR. This can be seen from Fig. 3 where the antenna nulls are not perfectly aligned with the AOAs of the interfering signals. It is well-known that the optimum beamforming weight vector is given by the classical Minimum Variance Distortionless Response (MVDR)[4] adaptive beamformer:

$$w_i = \mu M^{-1} s_i \tag{3}$$

where M is the covariance matrix formed from the interference and noise, s_i is the steering vector which points the array in the direction of the desired signal i, and μ is a normalization constant. Even though the MVDR beamformer is optimal in the sense of SINR, it cannot be implemented in the ad hoc sensor network scenario: M cannot be calculated because the desired signal is mixed together with the interference and noise, while determining s would require knowledge of the precise relative positions of the nodes in the cluster as well as the AOA of the desired signal.

We propose a hybrid beamforming approach which combines the virtual array advantages of r-ICA with the optimal SINR performance of the MVDR beamformer. ICA is used to perform an initial separation of the mixtures and to estimate quantities needed for use in the MVDR beamformer. The MVDR beamformer then further improves the signal separation by maximizing the SINR. First, ICA is performed on the signal mixtures. As an output of ICA, we obtain an estimate of the mixing matrix. We can then form *generalized steering vectors* from the rows of the mixing matrix.[5] As can be seen from Fig. 4, the generalized steering vectors steer the main lobe of the antenna response towards the desired signal (similarly to conventional array steering vectors), but they also place nulls at the AOAs of the interfering signals.

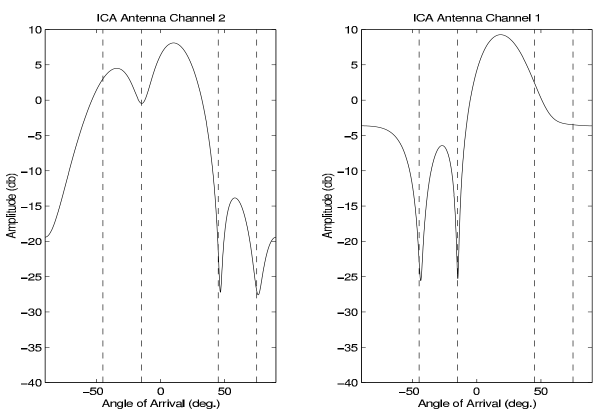

Fig. 4. Simulated 1-D virtual antenna array angular responses (relative to single element) for the ICA beamformer. The array consisted of 6 randomly spaced elements. A different row of the ICA demixing matrix was used as the antenna weight vector in each plot. Output SINRs for the two speech signals were 25 db and 40 db. Unprocessed SINRs were 9 db and -9 db for initial antenna weights set to unity. Signal sources were baseband speech signals with 10% gaussian noise added to each mixture. Dashed lines indicate the angles of arrival for the two signals and their multipaths. Each signal had two AOAs corresponding to the two different multipaths.

Thus using ICA we can obtain generalized steering vectors without the need for a calibrated array or knowledge of the signal AOAs. In addition, we can calculate the covariance matrix M of the interference and noise mixtures by taking advantage of the fact that ICA separates all of the signals simultaneously into parallel output channels. We can identify which ICA output contains the reference signal and then form the covariance matrix from the remaining outputs which contain only interference signals. By inserting the generalized steering vectors and covariance matrix calculated using ICA into the MVDR beamformer expression above, we obtain the ICA-MVDR weight vector, which is SINR optimal, using an ad hoc uncalibrated virtual antenna array and without knowing the signal AOAs. Conversely, if a calibrated array is available, then this method can be used to find the AOA of a desired signal.

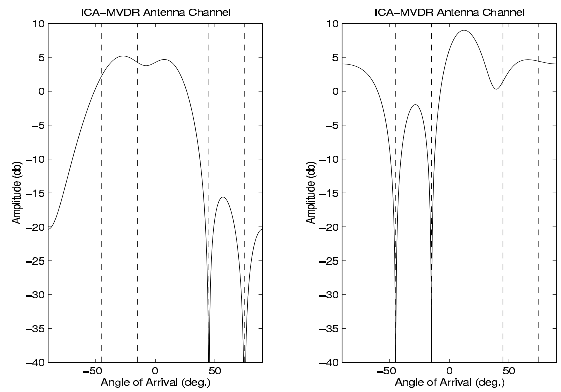

Fig. 5. Simulation results for ICA-MVDR beamformer using rows of the ICA demixing matrix from Fig. 4 as generalized steering vectors. Antenna parameters and signals were the same as in Fig. 4. Output SINRs for each signal were 54 db and 42 db. Unprocessed input SINR values for each signal were 9 db and -9 db for initial antenna weights set to unity. Signal sources were baseband speech signals with 10% gaussian noise added to each mixture. Dashed lines indicate the angles of arrival for the two signals and their multipaths. Each signal had two AOAs corresponding to the two different multipaths. Nulls in the antenna responses centered on the interfering signals are deeper compared to Fig. 4.

Figs. 4 and 5 compares results of r-ICA and ICA-MVDR beamforming from a simulation of two signals, each with two multipaths, arriving with different AOAs at a linear virtual array formed from six randomly positioned nodes. The two signals consisted of two baseband speech signals sampled at 8 khz. Gaussian noise with mean amplitude of 10% was added to each signal mixture in order to simulate receiver noise. The signal-to-interference ratios (SINR) for the two received signals before processing were 9 and -9 db, respectively. The angular responses of the linear antenna array using different ICA weight vectors are shown in Fig. 4. In the lefthand plot it can be seen that ICA placed nulls at the AOAs of the two multipaths corresponding to the second signal. (Dashed vertical lines in each plot indicate the AOAs for the multipaths. The two AOAs on the left in each plot correspond to the first signal's multipaths.) Similarly, the second ICA weight vector in the righthand plot placed nulls on the multipaths for the first signal. The ICA SINRs for the two signals were 25 db and 40 db, respectively. The outputs were well-separated with very little audible cross-talk between the signals. For these examples we used the Joint Approximate Diagonalization of Eigenmatrices (JADE)[6] ICA algorithm. Fig. 5 shows the ICA-MVDR beamformer angular antenna responses. The output SINR for the two signals increased to 54 and 42 db, respectively. The improvement in SINR compared to ICA is due to the deeper nulls centered on the interfering signals.

Frequency Domain ICA-MVDR

A limitation of the time-domain ICA and ICA-MVDR adaptive beamforming approaches described above is that they are effective only for instantaneous mixtures, not convolutive mixtures due to multipath and channel delay spreading. The relative delays between multiple versions of a signal arriving at the antenna must be less than the inverse of the signal bandwidth. Various techniques have been described for ICA processing of convolutive mixtures, including training equalization filters in both the time and frequency domains.[7] In order to handle the general case of delayed multipaths and channel delay spreading described by Eq. 1, we describe here an extension of ICA-MVDR to the frequency domain.

If we fourier transform Eq. 1, the convolution operations become multiplications and the problem is converted into separating instantaneous mixtures. Since we need time-sampled data for ICA, we perform a sliding window short time fourier transform (STFT) on Eq. 1 resulting in

$$Y_m(\omega,t) = \sum_k \sum_p c_{mkp} B_{mkp}(\omega) S_k(\omega,t) + N_m(\omega,t) \tag{4}$$

in which the instantaneous mixtures $Y_m(\omega,t)$ are indexed by both channel index m and frequency bin ω. ICA is then performed on each frequency bin ω, resulting in estimates for each source signal STFT frequency component $S_p(\omega,t)$. (Although ICA must be performed multiple times, each ICA is done on a much smaller number of time samples because of the STFT time window.) Since ICA solutions are degenerate with respect to the output port ordering of the separated signals, port swapping guided by signal tracking must be used to enforce signal consistency across the frequency components. (See Sec. 5.) After port swapping, the estimated time-frequency distributions $S_p(\omega,t)$ can be transformed using the inverse STFT to optain the separated source signals $s_p(t)$. Using this method, different relative delays and weighting factors for multiple copies of the same signal caused by multipath and/or channel delay spreading can be handled by ICA. Another advantage is that interference excision and other filtering operations can be performed in the time-frequency plane before the inverse STFT is performed.[8]

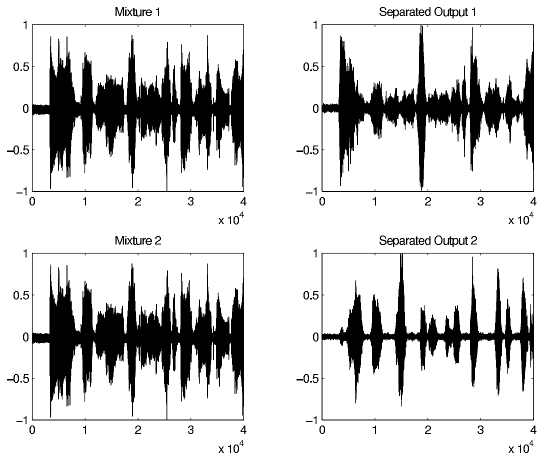

Fig. 6. Time plots for STFT ICA separation of two 8 Khz speech signals with two multipaths each, 12-tap random phase channel filters, and 10% gaussian noise added to each channel mixture. The signals were received by a 4-element antenna array. Mixtures are on the left and separated sources are on the right.

Results of STFT ICA processing are shown in Fig. 6. Two baseband speech signals sampled at 8 Khz with two multipaths each were mixed together using a 4-element randomly spaced linear antenna array. 10% gaussian noise was added to the mixtures. Delay spreading channels for each of the multipaths were simulated using 12-tap filters in which each coefficient had an amplitude of 1 and a random phase value. As can be seen from Fig. 6, good separation between the two speech signals was obtained. In terms of audio quality, very little crosstalk between speakers could be heard. The sound quality was somewhat degraded, but the speakers could still be clearly understood.

ICA-MVDR adaptive beamforming can also be extended to the frequency domain. We simply apply ICA-MVDR to each frequency component separately and then port swap to group together frequency components belonging to the same signal source, as discussed above and in Sec. 5. We can then form the covariance matrices necessary for MVDR beamforming for each frequency bin:

$$M_{pq}(\omega) = \sum_t \hat{S}_p(\omega,t) \hat{S}_q^*(\omega,t) \tag{5}$$

The ICA-MVDR beamformer weight vector for frequency ω and output channel i is then given by

$$W_i(\omega) = M(\omega)^{-1} A_i(\omega)$$ (6)

where $A_i(\omega)$ is the generalized steering vector obtained from ICA's estimate of the mixing matrix for frequency ω (Eq. 4). The ICA-MVDR frequency domain solution for $S_i(\omega,t)$ is obtained from the inner products of $W_i(\omega)$ and the mixtures $Y_m(\omega,t)$. The separated time-domain sources are then given by the inverse STFT of $S_i(\omega,t)$.

5. Port Swapping

An issue common to all ICA signal separation methods is an inherent ambiguity in the ordering of the output channels. The outputs at the end of each processing frame may be arbitrarily permuted. These permutations can be compensated by tracking features of the separated signals, such as kurtosis and mean frequency, and swapping the output ports so as to always assign each output signal to the same output port, as long as the statistics of the signal are stationary. Alternatively, the rows of the demixing matrix can also be tracked for permutation compensation. The same techniques can also be used to maintain the correct ordering of the rows of the covariance matrix relative to the generalized steering vector s in the ICA-MVDR beamformer. In our time-domain r-ICA and ICA-MVDR simulations we used tracking of output signal kurtosis and mean frequency for port swapping when processing multiple blocks of data.

In frequency domain ICA, port swapping must be performed on both the frequency bin and block levels. For the frequency bins we used the principle that the time-envelopes of adjacent frequencies in the STFT of a signal tend to be similar to port swap the individual frequency components and maintain the coherence of each output signal's STFT. After the STFTs are inverted to recover the output signals, the signals must be port swapped to resolve the block by block permutation ambiguity.

6. Conclusions

We have described a hybrid approach to adaptive beamforming which combines the flexibility of blind source separation based on ICA with the performance of classical non-blind maximum SINR adaptive beamforming. ICA is used to first estimate source and interference signals as well as the mixing matrix. Rows of the mixing matrix are then used as generalized steering vectors for a second stage consisting of an optimum SINR MVDR beamformer. The MVDR interference covariance matrix is calculated using the ICA-separated signals. This allows the MVDR solution to be calculated without calibration of the antenna array, which allows virtual antenna arrays to be formed dynamically. By using ICA training signals designed for rapid ICA convergence, changing environmental conditions can be compensated rapidly. These techniques can be used for collaborative beamforming using virtual uncalibrated antenna arrays in which multiple nodes share antenna, spatial diversity, and battery resources. Of course, ICA-MVDR beamforming can also be used for conventional fixed antenna arrays. If the array is calibrated, ICA-MVDR beamforming can be used to determine the angles of arrival of signals by locating nulls in the ICA-MVDR antenna angular response.

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