



Review on Acoustic Source Localization Techniques

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ABSTRACT

Acoustic Source Localization (ASL) means to estimate the position of the source, emitting sound. It has a wide application area. Based upon the literature survey, ASL techniques have been broadly classified as Time Delay Estimation (TDE), Beamforming, High Spectral Resolution, Energy aware and Binaural based. There are different methods based upon these classifications such as Cross correlation, Generalized Cross Correlation (GCC) and Adaptive Eigen Value decomposition (AED). It has been shown by the researchers that different techniques have proved to be effective in different environment conditions. GCC and AED have better performance in ideal propagation scenarios or where the reverberation is low. In moderate to high reverberation channels, SRP-PHAT has been proved to give more accurate results than GCC but the Computational complexity has always been a challenge here. High spectral resolution methods are quite complex but have given better resolution over other techniques and mainly preferred for narrowband signals to find their Direction of Arrival (DOA).

Key words: Acoustic Source Localization, Time Delay Estimation, Cross correlation, Generalized Cross Correlation, Maximum Likelihood, Adaptive Eigen Value Decomposition, Steered Response Power, Phase Transform

INTRODUCTION

The aim of Acoustic Source Localization (ASL) system is to estimate the position of sound sources in an environment by analyzing the sound field with a microphone array, a set of microphones arranged to capture the spatial information of sound. In general, most ASL techniques rely on the fact that an impinging wave front reaches one acoustic sensor before it reaches another [11].

ASL has wide application areas, as automatic camera steering in conference hall, surveillance, teleconferencing, speech enhancement, health monitoring, industrial and manufacturing automation, traffic control, hearing aid devices, and human computer interaction, sonar, radar, mobile phone location finding, navigation and global positioning systems, localization of earthquake epicentres and underground explosions, robots, micro seismic events in mines and sensor networks [14] [21] [7] [11].

ACOUSTIC SOURCE LOCALIZATION (ASL) TECHNIQUE

These can be broadly divided into TDE, Beamforming, Subspace methods, Energy aware and Binaural based.

Time Delay Estimation (TDE)

TDE localization is a two step procedure, first is to estimate the time difference of arrival of the signal at the microphones pairs as shown in Fig.1. Second stage is to calculate location of source from TDOA using appropriate algorithm like spherical interpolation, hyperbolic intersection. TDE methods are also called TDOA methods or interaural time difference (ITD). TDOA based methods with high sampling rates are suitable for near field and far field high accuracy wideband source localization. Yue kan [1] has given a method for localization at low sampling rate based on five element cross microphone array. Minimum requirement for 2D and 3D source localization is 3 and 4 microphones respectively to avoid front-back confusion effects in isotropic antennas [7]. This technique is used in bulk as it is computationally less burdensome as compared to beamforming [23]. Uncertainty in TDOA leads to error in localization, which is a very tough task due to reverberation, background noise and short observation interval. Equation complexities and convergence of non linear equation are the major issues at second stage. Different methods based on TDE are CC, AED, GCC, LMS and ASDF have been developed to improve their performance in low SNR (Signal to Noise Ratio). In an echo free field environment source to microphone signal is shown in Fig.1.

In Fig.1, $r_1(t)$ and $r_2(t)$ are the signals received at microphones 1 and 2 respectively due to source $S(t)$ and can be represented using Eq. (1) and Eq. (2) as given below.

$$r_1(t) = \alpha S(t) + n_1(t) \tag{1}$$

$$r_2(t) = \alpha S(t - \tau) + n_2(t) \tag{2}$$

where α is attenuation factor, $0 \leq t \leq T$, T is the observation interval, $c\tau$ is the extra distance wave has to travel to reach microphone 2 with respect to microphone 1, where c is the speed of sound in the medium and τ is relative delay of $r_2(t)$ with respect to $r_1(t)$, $n_1(t)$ and $n_2(t)$ are noises added to the source signal while travelling to microphone array[9][11].

Cross Correlation

It is the most basic method of TDE [7]. It correlates the microphone output and considers the time argument that corresponds to maximum in the $R_{r_1r_2}(\tau)$ as the estimated delay. CC can be modelled by:

$$R_{r_1r_2}(\tau) = E[r_1(t)r_2(t - \tau)] \tag{3}$$

$$\tau_{cc} = \arg \max[R_{r_1r_2}(\tau)] \tag{4}$$

Generalised Cross Correlation (GCC)

GCC based source localization is most popular among TDOA due to its accuracy and moderate computational complexity, which was proposed by Knapp and G. Carter [27] as an improvement over CC. It is also known as Cross-Power Spectrum Phase (CSP) [26][10].

$$R_{r_1r_2}(\tau) = \int_{-\infty}^{\infty} \psi(f)G_{r_1r_2}(f)e^{j2\pi f\tau}df, \tag{5}$$

$$\tau_{cc} = \arg \max[R_{r_1r_2}(\tau)] \tag{6}$$

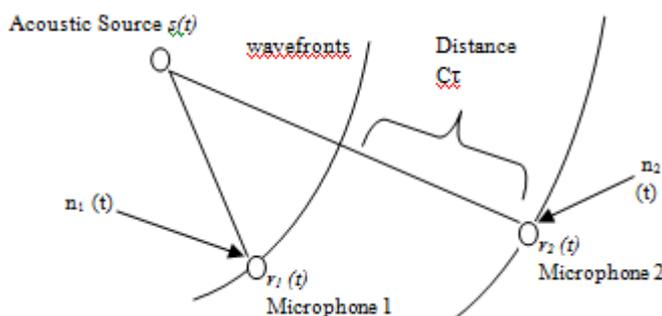


Fig. 1 Time-delay associated with two microphones

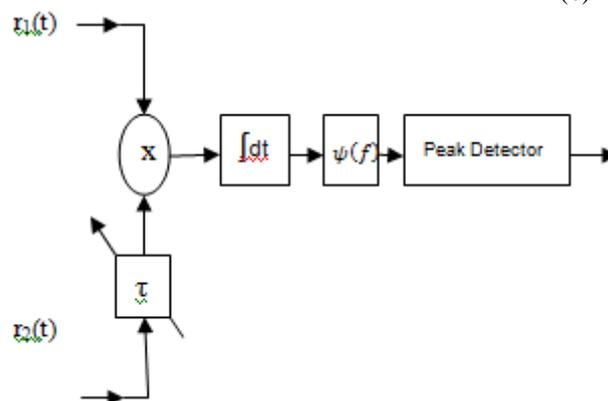


Fig. 2 Generalized Cross-correlation method

In equation 5, cross correlation is found using the inverse DFT of the cross power spectrum of the two signals where $G_{r_1r_2}(f)$ is the cross spectrum of the two received signal at the microphone array, ψ is the weighing function and τ_{cc} is the delay corresponding to maximum value of $R_{r_1r_2}(\tau)$. GCC assumes an ideal free field model and performs well in moderate noise and reverberation only. The ambiguity inherent in TDOA estimation in reverberant environment through GCC maxima search can be attributed to unknown number of signal path from source to microphones. To solve the ambiguity Maria et al [17] have given improved TDOA Disambiguation technique. Zhang [16] has given A Two Microphone-Based Approach for Source Localization of Multiple Speech Sources to limit the number of resources required.

The correlation peak is sharpened using different weighing function (shown in Table 1), to improve the resolution of TDE.

Table -1 List of the Weighing Functions used in GCC

Name	Value
CC	$\psi_{CC}(f) = 1$
PHAT	$\psi_{PHAT}(f) = 1/ G_{r_1r_2}(f) $
ML	$\psi_{ML}(f) = \frac{1}{ G_{r_1r_2}(f) } \frac{ \gamma_{r_1r_2}(f) ^2}{1- \gamma_{r_1r_2}(f) ^2}$, where $ \gamma_{r_1r_2}(f) ^2 = \frac{ G_{r_1r_2}(f) ^2}{G_{r_1r_1}(f)G_{r_2r_2}(f)}$
ROTH	$\psi_{Roth}(f) = 1/G_{r_1r_1}(f)$ or $1/G_{r_2r_2}(f)$
SCOT	$\psi_{scot}(f) = 1/G_{r_1r_1}(f)G_{r_2r_2}(f)$

Cross correlation is a special case of GCC where the weighing function is 1.

ML has proved to be optimal and robust scheme for coherent source signal. Its weights the cross-spectral phase according to the estimated cross-spectral phase when the variance of the estimated phase error is the least. $|\gamma_{r_1 r_2}(f)|^2$ is the magnitude coherency function. The more weight is given to the high correlation frequencies and those corresponding to near zero correlation are de-emphasized or in other words, it attenuates the frequencies fed to correlator where SNR is low. However, it gives a complicated non linear optimisation problem when multiple sources are encountered and doesn't even give satisfactory performance in reverberant environment as it works on ideal propagation model. Dranka [2] has provided us with Robust Maximum Likelihood Acoustic Energy Based Source Localization in Correlated Noisy Sensing Environments. Zhang [21] has given maximum likelihood framework for ASL and beamforming in distributed meeting application, to capture superior speech quality using microphone arrays.

PHase Transform (PHAT) has been widely used due its ability to avoid spreading of the peak and anti-jamming ability, while calculating cross correlation, therefore uncertainty in TDOA reduces. Only phase information is retained after cross spectrum is divided by its magnitude [23]. With time PHAT weighing became very popular which is also called pre-whitening filter. When used with GCC, it is called GCC-PHAT.

Adaptive Eigen Value Decomposition

AED another popular method for ASL, introduced by Benesty [25], working on reverberation model unlike GCC which works on ideal propagation model. The AED algorithm actually amounts to a blind channel identification problem, which then seeks to identify the channel coefficients, corresponding to the direct path elements. The extension of the AED in the case of multiple microphones was proposed by Huang & Benesty, and it is called Adaptive Blind Multichannel Identification (ABMCI) [11]. The eigenvector corresponding to the minimum Eigen value of the covariance matrix of the microphone signals contains the impulse responses between the source and the microphone signals and therefore all the information we need for time delay estimation.

We assume system LTI, and then we can write

$$r^T_1(n)h_2 = r^T_2(n)h_1 \quad (7)$$

Where

$$r_i(n) = [r_i(n) \ r_i(n-1) \dots \ r_i(n-M+1)], \quad i=1,2$$

are the signal samples at the microphone outputs and 'T' is transpose of matrix. The impulse response vector of length are defined as

$$h_i \equiv [h_{i,0} \ h_{i,1} \ \dots \ h_{i,M-1}]^T \quad i=1,2 \quad (8)$$

Linear relation in Eq.(7) follows from fact that $r_i = s * h_i$, $i = 1,2$

$$r_1 * h_2 = s * h_1 * h_2 \quad (9)$$

The covariance matrixes of the two signal is

$$R = \begin{bmatrix} R_{r_1 r_1} & R_{r_1 r_2} \\ R_{r_2 r_1} & R_{r_2 r_2} \end{bmatrix} \quad (10)$$

$$R_{r_i r_j} = E\{r_i(n)r_j^T(n)\} \quad i, j = 1,2$$

Considering a $2M \times 1$ vector $u = \begin{bmatrix} h_2 \\ -h_1 \end{bmatrix}$

It can be seen that $Ru=0$, which means that the vector u is the eigenvector of the covariance matrix R corresponding to the eigen value 0.

Average Square Difference Function (ASDF)

The ASDF method is based on finding the position of the minimum error square between the two received noisy signals and considering this position value as the estimated time delay.

$$R_{ASDF}(\tau) = \frac{1}{N} \sum_{n=0}^{N-1} [r_1(n) - r_2(n + \tau)]^2 \quad (11)$$

$$\tau_{ASDF} = \arg \min [R_{ASDF}(\tau)] \quad (12)$$

This method has a drawback that its accuracy drops when the noise at two sensors is correlated with the desired signal, high reverberation level, background noise (These all can be combined to Low SNR), observation interval is small or noise is not Gaussian. In many practical speech processing applications, the Discrete Fourier Transform (DFT) coefficients are computed from finite duration signals, which make the Gaussian assumption less favourable choice for signals whose time domain distributions are non-Gaussian. Souden et al [14] has consider both categories, ASDF and (with AMSF average magnitude sum function) and cross correlation using arbitrary number of microphones.

Beamforming

Beamformer is used to scan at predefined location, where source is located. The point corresponding to source location gives the maximum power output.

In Beamforming, the microphones output is delayed and added in such a way that signals from desired direction add coherently and from other direction and noise add incoherently. Delay and sum beamformer are the simplest one whereas others like capon beamformer are more advanced, which involves filter, delay and sum [11].

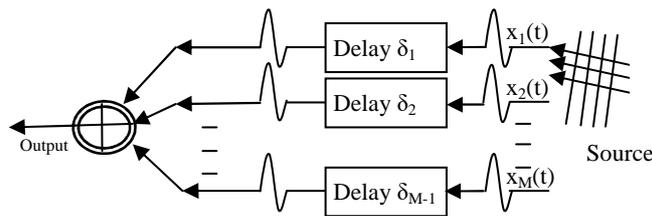


Fig. 3: Delay sum beam forming method

The signal received at microphone is given by equation below:

$$r_m(t) = s(t) * h(\vec{d}_s, t) + n_m(t) \quad (13)$$

$s(t)$ is the source signal, $h(\vec{d}_s, t)$ is the impulse response of the path from source to microphone. Output of a beamformer is summation of the microphone signals after adding appropriate delay to make them coherent.

$$y(t, \delta_1, \delta_2 \dots \delta_M) = \sum_{m=1}^{m=M} r_m(t - \delta_m) \quad (14)$$

In frequency domain it is given by

$$Y(\omega, \delta_1, \delta_2 \dots, \delta_M) = \sum_{m=1}^{m=M} G_m(\omega) R_m(\omega) e^{-j\omega\delta_m} \quad (15)$$

This leads to reinforcement of signal from particular direction and therefore called steered response Power (SRP)[5][6][20]. The power in frequency domain is defined as

$$P(\delta_1, \delta_2 \dots, \delta_M) = \int_{-\infty}^{\infty} Y(\delta_1, \delta_2 \dots \delta_M) Y^*(\omega, \delta_1, \delta_2 \dots, \delta_M) d\omega \quad (16)$$

On substituting the value of Y from Eq. (15) in Eq. (16) and on rearrangement we get

$$P(\delta_1, \delta_2 \dots, \delta_M) = \sum_{k=1}^{k=m} \sum_{l=1}^{l=m} \int_{-\infty}^{\infty} (G_k(\omega) G_l^*(\omega)) (X_k(\omega) X_l^*(\omega)) e^{j\omega(\delta_l - \delta_k)} d\omega \quad (17)$$

$$(\delta_l - \delta_k) = \tau_l - \tau_k \quad (18)$$

Note that integral converges in practice, the microphone signal and filters have finite energy and therefore the summation has been interchanged with integration.

$$P(\delta_1, \delta_2 \dots, \delta_M) = \sum_{k=1}^{k=m} \sum_{l=1}^{l=m} \int_{-\infty}^{\infty} (\psi_{kl}(\omega) (X_k(\omega) X_l^*(\omega)) e^{j\omega\tau_{lk}} d\omega \quad (19)$$

$\psi_{kl}(\omega)$ is the weighing function.

$$R_{kl} = \frac{1}{2\pi} \int_{-\infty}^{\infty} (\psi_{kl}(\omega) (X_k(\omega) X_l^*(\omega)) e^{j\omega\tau_{lk}} d\omega \quad (20)$$

This peak can be calculated by several methods like gradient search. The major limitation here is computational complexity as objective has to be calculated at every point in space. Improvement has been done using various methods as SRC (stochastic region contraction), coarse to fine region contraction (CFRC). Marti [5] has suggested modified SRP using coarser spatial grids instead of costly grid search procedure. Lima [3-4] has proposed Volumetric-SRP (V-SRP), deploying a sparser volumetric grid to achieve significant reduction in computational complexity without sacrificing accuracy of location estimates. By appending a fine search step to the V-SRP, its refined version (RV-SRP) improves on the compromise between complexity and accuracy. Yan [6] has accelerated SRP method using clustering search. Yongyun [18] has given ASL using region selection which reduces the complexity.

Beamforming methods are single stage, as localization here is one step process unlike TDE. Instead of working on pair wise time delay, it exploits the multitude of microphones to overcome the limitation given by early decision and reverberation. This method allows one to work on lower data segments and to localize multiple speakers, where SRP will peak multiple times. SRP-PHAT is a popular method, in which PHAT weighing function is used.

High Spectral Resolution Methods

It is based upon the spatio-spectral correlation matrix which can be derived from the signals received by the microphone array. First it decomposes the cross correlation matrix of microphone signals into Signal and noise subspace using Eigen value decomposition and then search is performed using Noise or signal Subspace to find the most likely DOA. DOA based beamforming and subspace methods typically need large number of microphones for high accuracy narrowband sound source localization in far field cases [7]. They also have higher processing need in comparison to other method. This category includes autoregressive modeling, minimum variance spectral estimation. Some of these methods are limited to far-field, which means the sensors are supposed to be far away from the sound source, and linear array situation, where the microphone array are deployed in a line. It also needs time to search in the whole space for maximum. The maximum is supposed to be a sharp maximum and can be easily found. They are preferred for the narrowband signals. ESPRIT [19] (Estimation of Signal parameters via

Rotational Invariance Technique) and MUSIC [19] (Multiple Signal Classification) are examples of this class. MUSIC is very popular and widely used. First it was used in spectral estimation to estimate the frequencies and characteristics of the wave fronts and later developed for DOA estimation for narrowband signal. With time MUSIC has been modified and application areas have increased. It can also be used for with wideband source by applying dividing entire band into segments [19]. Yan [12] has given new hybrid algorithm for ASL.

BINAURAL BASED

These algorithms used are inspired from the neurology and popular with name Head Related transfer function (HRTF). This is commonly used technique for localization in commercial Robots. The physical system is constructed using manikin head and two microphones placed on the body. In a dual-microphone array it is usually assumed that the difference in the two channels is limited to a small time delay (or linear phase in frequency domain) and therefore the cross-correlation is peaked at the time corresponding to the delay. Thus, methods that search for extrema in cross-correlation waveforms are commonly used. The time delay approach is based on the assumption that the sound waves propagate along a single path from the source to the microphone and that the microphone response of the two channels for the given source location is approximately the same. In order for this to hold, the microphones should be identical, co-aligned, and, near each other relative to the source. In addition there should not be any obstructions between or near the microphones. This technique also is used by field biologist to study animal presence and their behaviour. Ali et al [7] has purposed N-dimensional N-microphone sound source localization using ILD-TDE-HRTF methods simultaneously, which has lead to reduction in microphone requirement for localization.

Energy Based or Interaural Level Difference (ILD) or Intensity Level Difference (ILD)

In these algorithms, energy measured at individual sensors is used for localization. It is known that in free space, acoustic energy decays at a rate that is inversely proportional to the distance from the source. Therefore, if we take simultaneous acoustic energy measurements emitted from an Omni directional acoustic source at different, known sensor locations, then it is possible to infer the location of the source based on these readings. It requires relatively few computations and consumes little communication bandwidth, and therefore is suitable for low power operations [2] [15].

Let there be N sensors deployed in a sensor field in which a target emits acoustic signals. The signal energy measured on the i^{th} sensor over a time interval t , denoted by $y_i(t)$, can be expressed as follows:

$$y_i(t) = \frac{1}{T} \sum_{t-\frac{T}{2}}^{t+\frac{T}{2}} r_i^2(t) \quad (21)$$

The time window is $T = M/f_s$ where M the number of sample points per time window is, f_s is the sampling frequency.

$$y_i(t) = \frac{1}{T} \sum_{t-\frac{T}{2}}^{t+\frac{T}{2}} s_i^2(t) + \frac{1}{T} \sum_{t-\frac{T}{2}}^{t+\frac{T}{2}} v_i^2(t) \quad (22)$$

where $r_i(t)$ is the received signal at the sampling point, $s_i(t)$ is the received signal without noise, and $v_i(t)$ is the AWGN (Additive White Gaussian Noise). Haengi [24] has given other challenges has opportunities in wireless sensors networks.

Time of Arrival (TOA)

This is a very basic technique where distance is calculated by time multiplied by speed. When the two microphones are taken as shown in Fig. 4, there is back forth ambiguity which is resolved by taking third microphone into account as shown in Fig. 4. Accuracy is confined by Line of Sight (LoS) condition. Signal TOA measurement is relatively direct to acquire since the sensor node can determine the signal arrival time by simply identifying and locating a known preamble from transmitted source signal. When utilizing TOA measurements for source localization, it is often assumed that the source and sensor nodes cooperate such that the signal propagation time can be found at sensor nodes. However, such collaboration between source nodes and sensor nodes is not always available. Thus, without knowing the initial signal transmission time at the source, from TOA alone, the sensor is unable to determine the signal propagation time from its source to the measuring sensor. One way to tackle this problem is to exploit the difference of pair wise TOA measurements, i.e., time-difference of arrival (TDOA), for source localization [13]. The main limitation of this technique is that the source has to be known to the receiver and the developed system is only suitable for a small environment due to high path loss [13].

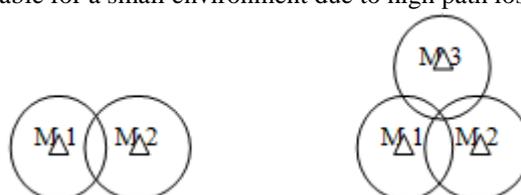


Fig. 4 TOA measurements using 2 and 3 microphones

CONCLUSION

Various Acoustic source localization techniques have been studied. Each technique has its limitation and therefore usage is application specific. It's up to researcher to choose a technique for his application. This field has attracted many researchers to work in real time, with complex urban environment or forest area or open terrain to improve the performance of existing technique.

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