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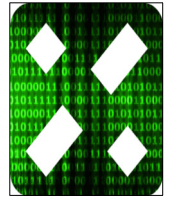
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Original software publication

Multisensor Time–Frequency Signal Processing MATLAB package: An analysis tool for multichannel non-stationary data



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ABSTRACT

The Multisensor Time–Frequency Signal Processing (MTFSP) MATLAB package is an analysis tool for multichannel non-stationary signals collected from an array of sensors. By combining array signal processing for non-stationary signals and multichannel high resolution time–frequency methods, MTFSP enables applications such as cross-channel causality relationships, automated component separation and direction of arrival estimation, using multisensor time–frequency distributions (MTFDs). MTFSP can address old and new applications such as: abnormality detection in biomedical signals, source localization in wireless communications or condition monitoring and fault detection in industrial plants. It allows e.g. the reproduction of the results presented in Boashash and Aïssa-El-Bey (in press) [2].

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Code metadata

Current code version	1.1
Permanent link to code/repository used for this code version	https://github.com/ElsevierSoftwareX/SOFTX-D-17-00097
Code Ocean compute capsule	https://doi.org/10.24433/CO.9224164.v1
Legal Code License	Apache License, 2.0
Code versioning system used	none
Software code languages, tools, and services used	MATLAB
Compilation requirements, operating environments & dependencies	–
If available Link to developer documentation/manual	https://github.com/ElsevierSoftwareX/SOFTX-D-17-00097
Support email for questions	tfsap.research@gmail.com

1. Motivation and significance

MTFSP is important in a wide range of applications where experiments produce a collection of measurements recorded from multiple sensors. Examples include multiple antennas in sonar and telecommunications; multiple electrodes that collect medical data; multiple acoustic sensors used for source localization; industrial plants fault detection and condition monitoring; geophysics, and speech data. In these contexts, multiple sensors can combine together to enhance the quality of information available about the phenomena generating the signals. Such sensors are typically

placed at different physical locations (spatially apart) to exploit space diversity using the spatial characteristics of the underlying process. Previous studies improved the performance of such systems by combining both the non-stationary characteristics of measured signals using high-resolution time–frequency distributions (TFDs) [1, Chapters 2 and 3] and the spatial information provided by sensor arrays [1, Chapter 8], [2].

The additional data information provided by MTFSP includes:

1. New patterns and features observable across the multisensor time–frequency (TF) matrix.
2. More precise automated separation of components (e.g. discriminating artifacts from seizures in EEG).
3. Estimating with accuracy the source or direction/location of an important event (e.g. origin of an abnormality or fault).
4. Performing a coherence/causality analysis across sensors/channels signals (e.g. propagation of a seizure location

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across channels corresponding to electrodes positions on the scalp).

MTFSP offers four techniques: (1) multisensor time–frequency transforms; (2) Automated component separation (ACS) based on MTFDs; (3) Direction of arrival (DOA) estimation using MTFDs and (4) Coherence/Causality analysis.

2. Software description

2.1. Multisensor time–frequency distributions (MTFDs)

MTFSP performs a multichannel TF transform using the MTFD matrix of multidimensional input signals. It uses some functions from the TFSAP Toolbox [3] which were extended to the multichannel case, as reported in [1] and [2].

2.1.1. Signal analysis in the monosensor case

The first step in MTFSP is to define TFDs in the monosensor case. Considering a non-stationary monosensor real signal $x(t)$ and its analytic associate $z(t)$, the Wigner–Ville Distribution (WVD) is defined as the Fourier Transform (FT) of the instantaneous autocorrelation function $K_z(t, \tau)$ i.e. [1]:

$$W_z(t, f) = \int_{\mathbb{R}} K_z(t, \tau) e^{-j2\pi f \tau} d\tau, \quad (1)$$

where $K_z(t, \tau)$ is defined as

$$K_z(t, \tau) = z\left(t + \frac{\tau}{2}\right) z^*\left(t - \frac{\tau}{2}\right). \quad (2)$$

For wider applicability, the WVD is convolved with a suitable selected 2D TF kernel, yielding:

$$\rho_z(t, f) = W_z(t, f) \underset{t f}{**} \gamma(t, f), \quad (3)$$

where $\rho_z(t, f)$ is the resulting quadratic TFD, $**$ indicates a double convolution in t and f , and $\gamma(t, f)$ is a TF smoothing kernel [2, Section 2.1]. Eq. (3) encompasses a wide range of old and new TFDs including the spectrogram.

2.1.2. Signals analysis in the multisensor case

Extending Eq. (3) to the multisensor case yields multichannel TFDs (MTFDs) for a signal vector $\mathbf{z}(t) = [z_1(t), \dots, z_m(t)]^T$, i.e. [2, Section 2], expressed as the following MTFD matrix:

$$\rho_{zz}(t, f) = \mathbf{W}_{zz}(t, f) \underset{t f}{**} \gamma(t, f), \quad (4)$$

where the double convolution $**$ is applied to each entry of the spatial WVD matrix $\mathbf{W}_{zz}(t, f)$ with individual elements $W_{z_i, z_j}(t, f) = \int_{\mathbb{R}} z_i\left(t + \frac{\tau}{2}\right) z_j^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi f \tau} d\tau$ for $i, j = 1, 2, \dots, m$, i.e.

$$\mathbf{W}_{zz}(t, f) = \begin{bmatrix} W_{z_1, z_1}(t, f) & W_{z_1, z_2}(t, f) & \cdots & W_{z_1, z_m}(t, f) \\ W_{z_2, z_1}(t, f) & W_{z_2, z_2}(t, f) & \cdots & W_{z_2, z_m}(t, f) \\ \vdots & \vdots & \ddots & \vdots \\ W_{z_m, z_1}(t, f) & W_{z_m, z_2}(t, f) & \cdots & W_{z_m, z_m}(t, f) \end{bmatrix}. \quad (5)$$

Examples of MTFD signal analysis appear in [2, Section 2.3.6].

2.2. Automated component separation (ACS) based on MTFDs

The aim of ACS methods is to process observations of mixtures acquired by multisensor arrays to recover the original unknown source signals. All identification or inversion methods based on output observations only are denoted “blind”; hence blind source separation (BSS) is a component of MTFSP based on MTFDs.

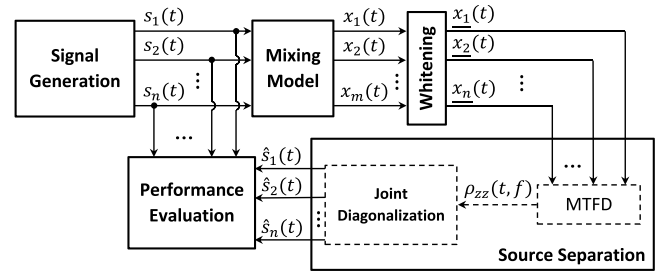


Fig. 1. Flowchart of the BSS algorithm based on MTFDs.

The formal objective of BSS is to estimate the n original signal sources $\mathbf{s}(t) = [s_1(t), s_2(t), \dots, s_n(t)]^T$ from the m received signal $\mathbf{x}(t) = [x_1(t), x_2(t), \dots, x_m(t)]^T$. Most BSS approaches, such as independent component analysis (ICA), assume that each source signal is statistically independent of others. The implemented method accounts for signal non-stationarity by using a TF approach combined with BSS to separate and recover the incoming signals. BSS methods can be divided into two classes according to the ratio between number of sources and sensors: (1) Over-determined case where the number of sources is greater than or equal to the number of sensors and (2) Under-determined case where the number of sources is less than the number of sensors. MTFSP includes both. The implementations are described below. Theoretical aspects are presented in [2, Sections 3.1 and 3.2].

2.2.1. Overdetermined ACS based on MTFDs

MTFSP includes the codes of BSS algorithms for (i) instantaneous mixtures and (ii) the more general case of convolutive mixtures (see Fig. 1).

(i) For the case of instantaneous mixtures, the data model is given by:

$$\mathbf{x}(t) = \mathbf{A} \mathbf{s}(t) + \boldsymbol{\eta}(t), \quad (6)$$

where the $m \times n$ matrix \mathbf{A} represents the propagation matrix or mixing matrix and $\boldsymbol{\eta}(t)$ is an additive noise vector whose entries are assumed as stationary, temporally and spatially white random processes, and independent of the source signals. Using this linear model, the MTFD matrix of an observed signal verifies:

$$\rho_{zz}(t, f) = \mathbf{A} \rho_{ss}(t, f) \mathbf{A}^H + \rho_{\eta\eta}(t, f), \quad (7)$$

where $\rho_{ss}(t, f)$ is the source MTFD matrix of $\mathbf{s}(t)$ whose entries are the auto- and cross-TFDs of the source signals. Then, the separation matrix is estimated via joint diagonalization (JD) and joint off-diagonalization (JOD) algorithms of a set of MTFDs matrices [2, Section 3.1]. A BSS experiment in the instantaneous mixture case using MTFDs is presented in [2, Section 3.1.4].

(ii) For the convolutive mixture case, the data model with K reflections verifies:

$$\mathbf{x}(t) = \sum_{k=0}^{K-1} \mathbf{A}(k) \mathbf{s}(t-k) + \boldsymbol{\eta}(t). \quad (8)$$

Unlike the instantaneous mixture case, the separation matrix in the convolutive mixture case is estimated as the joint block diagonalization (JBD) algorithm [4]. JD finds a diagonalization matrix such that the set of matrices is diagonal; JBD finds a diagonalization matrix such that the set of matrices is block diagonal (having the blocks on the main diagonal). An experiment of BSS in the convolutive mixture case using MTFDs is presented in [2, Section 3.2.3].

2.2.2. Underdetermined ACS based on MTFDs

MTFSP implements the underdetermined BSS in the instantaneous mixture case. Unlike the overdetermined case, the source estimation cannot be carried out by using linear operators, since the mixing matrix \mathbf{A} is not invertible. In order to tackle this in the underdetermined case, one of the two implemented methods assumes that the sources are disjoint in the (t, f) domain [5]; in other words, there is, at most, one source present at any point in the (t, f) domain. The TF disjoint assumption is a restrictive condition for real life applications such as audio and speech. When this condition does not hold, the separation performance degrades greatly at those overlapped (t, f) points [6]. As an alternative, a second implemented algorithm uses subspace projection methods, with sparsity assumption relaxed [2]; i.e., the TF representations of different sources can overlap to the extent that the number of active sources at any (t, f) point is strictly less than the number of sensors. A BSS experiment in the underdetermined case using MTFDs is presented in [2, Section 3.3.4].

2.3. DOA estimation based on MTFDs

This 3rd component of MTFSP implements an algorithm that estimates the spatial position of sources by assessing the DOA based on the received signal through an array of sensors (see Fig. 2).

2.3.1. TF-MUSIC Algorithm

The MULTiple Signal Classification (MUSIC) algorithm exploits the subspace structure of the array covariance matrix $\mathbf{R}_{xx} = \mathbb{E} \{ \mathbf{x}(t)\mathbf{x}(t)^H \}$ and the orthogonality between signal subspace and noise subspace to estimate the DOAs as described in [2, Section 4.1.1]. MUSIC performs an eigenvalue decomposition of the unknown covariance matrix \mathbf{R}_{xx} estimated as:

$$\hat{\mathbf{R}}_{xx} = \frac{1}{T} \int_0^T \mathbf{x}(\tau) \mathbf{x}^H(\tau) d\tau, \quad (9)$$

where T is the signal duration. The singular value decomposition of $\hat{\mathbf{R}}_{xx}$ is [2]:

$$\hat{\mathbf{R}}_{xx} = \hat{\mathbf{V}} \mathbf{A} \hat{\mathbf{V}}^H, \quad (10)$$

with $\hat{\mathbf{V}} = [\hat{\mathbf{v}}_1, \hat{\mathbf{v}}_2, \dots, \hat{\mathbf{v}}_m]$. Then, MUSIC estimates DOAs as the peaks of the spatial spectrum estimate expressed by:

$$P_{\text{MUSIC}}(\theta) = \frac{1}{\sum_{i=n+1}^m |\mathbf{a}(\theta) \hat{\mathbf{v}}_i|^2}, \quad (11)$$

where $\mathbf{a}(\theta)$ is a column vector of the steering matrix which depends on array geometry. MTFDs increase the effective signal to noise ratio (SNR) and provide a robust estimation of the covariance matrix with respect to noise by spreading the noise power while localizing the source signal power in the (t, f) domain. Thus, TF-MUSIC is defined by extending MUSIC for direction finding using the subspace decomposition of an averaged MTFD matrix ρ_{zz} as described in [2, Section 4.2.1].

2.3.2. TF-ESPRIT Algorithm

MTFSP contains a second DOA algorithm: ESPRIT (Estimation of Signal Parameters via Rotational Invariance Techniques) [2, Section 4.1.2]. ESPRIT exploits the rotational invariance in the signal subspace created by two arrays with a translational invariance structure as described in [2]. The steps are:

- Estimate $\hat{\mathbf{R}}_{xx}$ in Eq. (9) and get the eigenvector $\hat{\mathbf{V}} = [\hat{\mathbf{v}}_1, \hat{\mathbf{v}}_2, \dots, \hat{\mathbf{v}}_m]$.
- From the n principal eigenvectors, form the matrix $\mathbf{V}_s = [\hat{\mathbf{v}}_1, \hat{\mathbf{v}}_2, \dots, \hat{\mathbf{v}}_n]$. Then, form the matrices \mathbf{V}_1 and \mathbf{V}_2 such that:

$$\mathbf{V}_s = \begin{bmatrix} \mathbf{V}_1 \\ \mathbf{V}_2 \end{bmatrix} = \begin{bmatrix} \text{first row} \\ \text{last row} \end{bmatrix}. \quad (12)$$

- Solve $\mathbf{V}_2 = \mathbf{V}_1 \boldsymbol{\psi}$ to estimate $\boldsymbol{\psi}$.

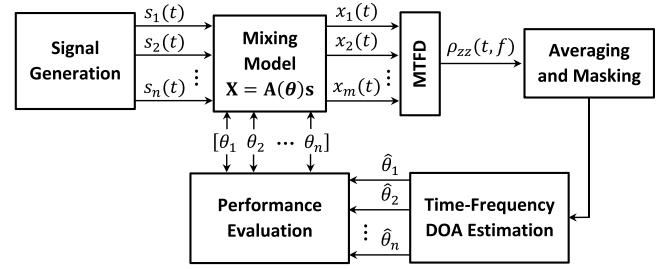


Fig. 2. Flowchart of the DOA algorithm based on MTFDs.

- Find the eigenvalues $\{\psi_1, \psi_2, \dots, \psi_n\}$ of $\boldsymbol{\Psi}$ to get the DOA estimates as:

$$\theta_i = \arccos \left(\frac{j\lambda \log \psi_i}{2\pi d} \right). \quad (13)$$

where λ and d are the signal wavelength and sensors spacing.

ESPRIT is more robust with respect to array imperfections than MUSIC. Similar to TF-MUSIC, one can extend ESPRIT to TF-ESPRIT for direction finding using MTFD matrices, by performing the subspace decomposition of an averaged MTFD matrix. MTFSP includes a TF-ESPRIT algorithm described in [2, Section 4.2.2]. An illustrating experiment of DOA estimation using MTFDs is presented in [2, Section 4.3] using the provided codes.

3. Cross-channel coherence/causality analysis

Interdependencies between multichannel signals can be quantified using linear correlation and coherence. For nonstationary data, extended phase synchrony metrics, such as time–frequency phase-locking value (PLV), can be used.

The PLV between two complex signals $z_i(t)$ and $z_j(t)$ can be estimated by:

$$P_{ij}(t, f) = \exp(j \varphi_{ij}(t, f)), \quad (14)$$

where $\varphi_{ij}(t, f)$ is the time-varying phase estimate based on a high-resolution quadratic TFD and defined by [2, Section 5]:

$$\varphi_{ij}(t, f) = \arg [\rho_{z_i, z_j}(t, f)^2]. \quad (15)$$

Cross channel synchrony can be quantified by averaging $P_{ij}(t, f)$ across time and frequency, such that [2, Section 5]:

$$\bar{P}_{ij} = \frac{1}{\text{Card}\{\Omega\}} \left| \sum_{(t,f) \in \Omega} P_{ij}(t, f) \right|, \quad (16)$$

where \bar{P}_{ij} is the ij th element of the mean PLV matrix $\bar{\mathcal{P}}$ that quantifies synchrony between the i th and j th sensors. Values in the $\bar{\mathcal{P}}$ matrix can vary from zero (no synchrony) to one (complete synchrony).

MTFSP can compute $\bar{\mathcal{P}}$ using two methods: conventional PLV, which only considers auto-TFDs, and extended PLV, which uses the full MTFD matrix. This can be done by typing:

```

Command Window
>> P_con = PLV(D, 'standard');
>> P_ext = PLV(D, 'extended');
>> figure; imagesc(abs(P_con)); axis xy;
fx >> figure; imagesc(abs(P_ext)); axis xy;
    
```

4. Illustration of DOA estimation using MTFDs

To illustrate capability, the example has four main stages, namely: signal generation, mixing model, conventional DOA estimation and TF DOA estimation. Each stage offers options to customize the script for different models and performance criteria.

4.1. Signal generation

Three different MATLAB functions namely: `signal_model`, `power_sig_model` and `sin_sig_model`, generate different synthetic signals (see package help page for details). In this example, `signal_model` is used to generate two linear frequency modulated (LFM) source signals by running the command:

```
fx >> [S, IF] = signal_model(n, f_end, f_start, N, fs);
```

To generate two crossing LFMs, one changing from 0.1 Hz to 0.4 Hz and the other from 0.4 Hz to 0.1 Hz, type:

```
fx >> s = signal_model(2, [0.4 0.1], [0.1 0.4], 256, 1);
```

4.2. Mixing model

Two MATLAB functions, namely `inst_model` and `conv_model`, can simulate mixed signals received on m uniform linear array sensors in an instantaneous or convolutive manner, respectively; e.g. `inst_model` is run by the command:

```
fx >> A = inst_model(n, m, rec_angle, lambda, d_spacing);
```

To generate $m = 4$ mixtures with an SNR of 30 dB using arrival angles of 10° and 30° with wavelength $\lambda = 150$ mm received through a uniform linear array with element spacing $d = 75$ mm, type the following command:

```
fx >> A = inst_model(2, 4, [10 30], 150, 75);
fx >> X = awgn(A*S, 30);
```

4.3. DOA estimation

A single provided MATLAB function, namely `doa`, performs conventional and extended TF DOA estimations utilizing different methods; `doa` is called in one line command:

```
fx >> P_DOA = doa(x, n, lamda, d_space, typ, varargin);
```

To estimate the DOA of the $m = 4$ received mixtures using conventional MUSIC and ESPRIT, type:

```
fx >> MUSIC = doa(X, 2, 150, 75, 'music', 0:0.1:40);
fx >> ESPRIT = doa(X, 2, 150, 75, 'ESPRIT');
```

To demonstrate MUSIC and ESPRIT DOA results, type:

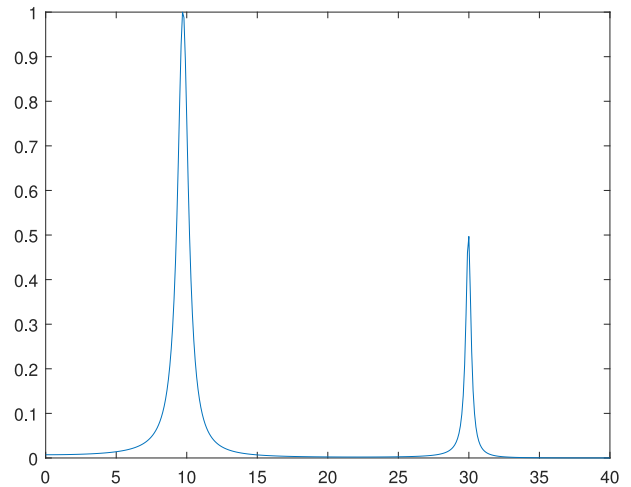


Fig. 3. DOA estimation using MUSIC algorithm.

```
fx >> plot(0:0.1:40, MUSIC);
fx >> disp(ESPRIT);
9.7411 29.9932
fx >>
```

Fig. 3 shows the resulting MUSIC spectrum with two peaks at the estimated angles of arrival.

To estimate the DOA using the extended TF-MUSIC and TF-ESPRIT, a single provided MATLAB function `mtfd` generates MTFD matrices using different methods. The `mtfd` function is called in one line command as follows:

```
fx >> D = mtfD(x, typ, varargin);
```

To compute the MTFDs matrices of the $m = 4$ received mixtures using the WVD, type in the command:

```
fx >> D = mtfD(X, 'wvd', 255, 256);
```

Then, MTFDs are averaged, masked; and high energy points are selected as follows (see Fig. 4):

```
fx >> % Averaged Auto-TFD
D_avg = zeros(256, 256);
for mm = 1:4, D_avg = D{mm,mm} + D_avg; end
D_avg = D_avg./4;
% Selection of high-energy (t,f) points
Tr = abs(D_avg) >= 0.2*max(max(D_avg));
[F_trace, ~] = find(Tr);
n_p = length(F_trace);
D_s = zeros(4, 4);
for m1 = 1:4
    for m2 = 1:4
        D_s(m1,m2) = (1/n_p).*sum(sum(D{m1,m2}.*Tr));
    end
end
```

Finally, the DOAs of the $m = 4$ received mixtures are estimated using extended TF-MUSIC and TF-ESPRIT by typing the command:

```
fx >> TF_MUSIC = doa(D_s, 2, 150, 75, 'tf-music', 0:0.1:40);
fx >> TF_ESPRIT = doa(D_s, 2, 150, 75, 'TF-ESPRIT');
```

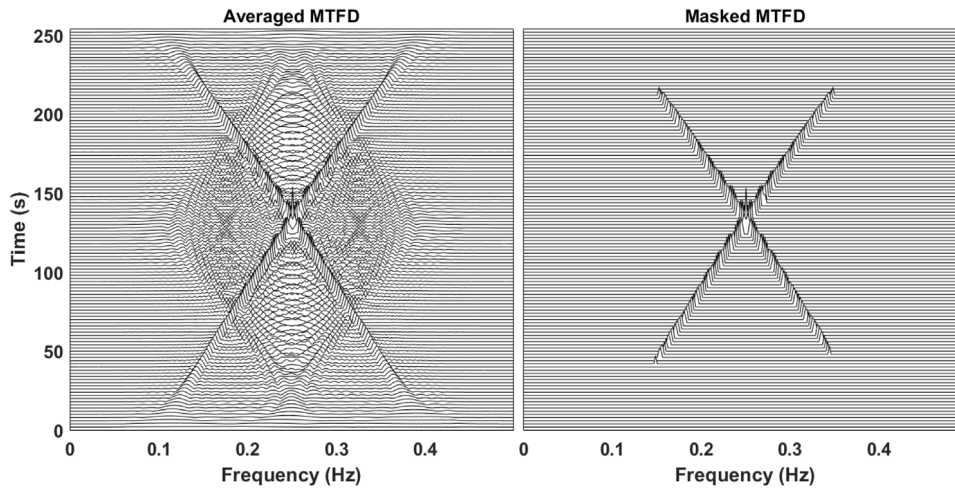


Fig. 4. Averaged and masked MTFDs matrices used for DOA estimation.

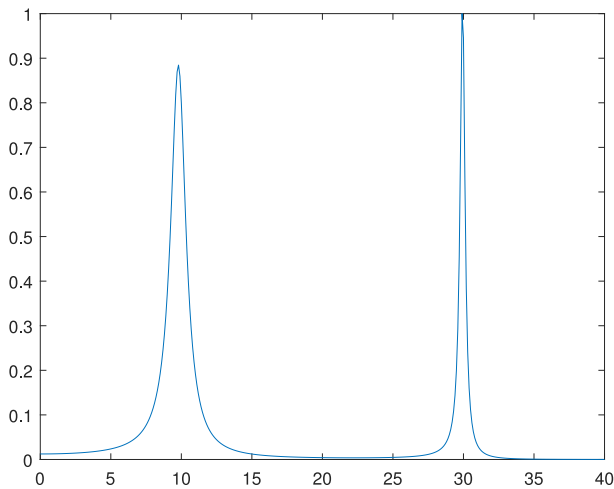


Fig. 5. DOA estimation using TF-MUSIC algorithm.

To demonstrate TF-MUSIC and TF-ESPRIT DOA results, type the command:

```

Command Window
>> plot(0:0.1:40, TF_MUSIC);
>> disp(TF_ESPRIT);
    9.8009    29.9504
fx >>

```

Fig. 5 shows the resulting TF-MUSIC spectrum with two peaks at the estimated angles of arrival.

5. Impact

MTFSP provides a precision tool for multichannel data analysis and non-stationary array signal processing. MTFSP can perform a coherence/causality analysis across channels in multichannel/multisensor. It allows users to easily exploit the wide range of TF tools available and incorporate them within MTFSP for their own projects. MTFSP uses some functions of the TFSAP toolbox [3], a well-known tool for non-stationary signal analysis and processing.

MTFSP can help address key problems in applications such as biomedical engineering and wireless communications as reported in studies such as [5–8]. In biomedical signal processing, the marriage of the two fields of TF analysis and array signal processing

leads to more efficiency in processing EEG signals in a variety of situations [2,9]; specifically, one can use TF-BSS and TF-MUSIC methods for artifacts removal and source localization [2, Section 6]. Such approach can be applied elsewhere e.g. to energy monitoring in industrial applications, such as tracking the electrical consumption of units in a factory to optimize performance (production versus electrical consumption) [10,11].

The studies cited in the list of references would have significantly benefited from the availability of this software package in terms of both speed and precision. In addition, TF-MUSIC and TF-ESPRIT have demonstrated in general higher accuracy and robustness than MUSIC, ESPRIT, and LORETA algorithms, and they therefore can offer more precise source localization in relevant real-life applications [12,13]. Similarly, future studies can use this package as a stepping stone, therefore saving researchers a significant amount of time in applications such as [14]. MTFSP also allows new applications where a precise use of MTFDs can extract critical additional information in data sets. For example, cross channel causality analysis allows researchers to track the time varying location of moving sources by combining spatial and TF information obtained by a multisensor array, one of the fundamental problems in wireless communication, seismology, biomedical signal processing and other areas.

6. Conclusions

MTFSP, a software tool for the analysis of multichannel non-stationary signals, extends conventional stationary array processing to the non-stationary case using high-resolution TF methods. The codes included in MTFSP can be used for a wide range of applications such as multisensors non-stationary signals analysis, ACS using MTFDs, DOAs based on MTFDs, blind system identification and equalization, source denoising or tracking of moving sources, and EEG source reconstruction.

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