On a method for testing ICA based Blind Source Separation algorithm performance applicable in audio-based On-Load Tap Changer diagnostics

Adnan Secic
DV Power Sweden / Faculty of Electrical Engineering and Computing, Zagreb, Croatia
adnan@dv-power.com

Nikica Hlupic
Department of Applied Computing
Faculty of Electrical Engineering and Computing, Zagreb, Croatia
nikica.hlupic@fer.hr

Igor Kuzle
Power System Department
Faculty of Electrical Engineering and Computing, Zagreb, Croatia
igor.kuzle@fer.hr

***Abstract* — The biggest challenges in using Blind Source Separation (BSS) algorithms, such as those based on Independent Component Analysis (ICA), arise from the inability to determine the reliability of the resulting independent components (signals). In sensitive areas, such as machinery diagnostics, such uncertainties could also have a negative impact on decision-making processes. For that reason, any additional confirmation that yields a better understanding of BSS algorithm capabilities and the issues that may arise from using this method in solving audio-based diagnostic problems is desirable. In this paper, the focus is placed on On Load Tap Changer (OLTC) audio-based diagnostics. The dominant audio signals that mix with the carrier of the useful diagnostic material, in this case, express stationary character. Given the fact that the targeted OLTC audio fingerprint usually represents a highly non-stationary signal that appears only in a certain period when compared to these interferences, it is possible to develop a source separation method based on a simple modeling approach. For that purpose, in this paper, a non-linear latest square curve fitting method was used for the extraction of the OLTC audio fingerprint, which was then used as a reference for testing the source separation efficiency of several different ICA algorithms.**

***Keywords*— OLTC; audio-based diagnostics; blind source separation; independent component analysis; BSS; ICA; curve fitting;**

I. INTRODUCTION

Blind Source Separation algorithms based on Independent Components Analysis prove to be very useful and effective in solving various problems in different areas, including audio processing, biomedical signal processing, image processing, telecommunications, etc. A very good review of BSS application specifics in different areas can be found in several chapters of the Handbook of BSS: ICA and applications [1]. Over the years, many different ICA algorithms have been developed. The ICALAB [2][3], a MATLAB Toolbox for signal processing (Ver. 3), used for ICA-based blind source separation in this paper, incorporates various ICA algorithms, such as: Fixed Point or FastICA algorithm [4], POWERICA (Power iteration for ICA) [5], EFICA (Efficient Variant of FastICA) [6], NG-FICA (Natural Gradient - Flexible ICA) [7], ThinICA [8], ERICA (Equivariant Robust Independent Component Analysis) [9], UNICA (Unbiased qNewton algorithm for Independent Component Analysis) [10], etc.

When it comes to audio-based machinery diagnostics, usually the problem comes down to isolating the useful audio signal from the audio mixture simultaneously formed by the targeted source and different "interfering" audio sources. The ability to isolate targeted audio signals enables the application of different diagnostic methods in order to validate the current "health" of the machine. The biggest challenge that arises here lies in the inability to determine the reliability of the BSS algorithm results. The above problem also reflects the reliability of the diagnostic results in the condition assessment process. An alternative to this approach could be found in the analog or digital filtering of the recorded audio signal mixture. However, this approach is often ineffective as the useful and the interfering signals can overlap over a certain frequency range, which prevents full removal of the external interference. Additional problems with the filtering approach arise from its inability to precisely define filter parameters and the proper thresholds. Such an approach would require the usage of adjustable filters for different situations. Also, additional problems occur with filtering the non-stationary signals, which can often be encountered in practice. For these reasons, taking into the consideration that the signal recording for the purpose of audio based machinery diagnostics is often performed in an uncontrolled environment, where different audio sources can be randomly activated, BSS seems to be the more logical approach to solving problems related to the audio-based machinery condition assessment.

In [11], the authors identify two major problems in the application of the ICA: (1) the finite sample size that induces statistical errors in the estimation process and (2) the real data never exactly follows the ICA model. Real audio mixtures are always affected by different factors starting with the imperfection of the recording system itself, to the delays and distortions resulting from reflections and absorptions of sound waves by different surfaces during their propagation in the analyzed space. However, there exist several developed methods that can help in estimating the performance of the ICA algorithm. In [11][12], the authors describe the statistical method for validating the independent components' reliability based on observing the results derived from the repeated application of the ICA algorithm on the given data set with different initial values. The basic idea behind the procedure is in observing the density of the clusters of the estimates formed by their mutual similarities. A similar procedure can be used in the estimation of the algorithm stability through the usage of the differently bootstrapped data sets. It should be noted that over the years, several different approaches addressing ICA components' reliability for different areas of application, such as those described in [13] and [14], have been developed.

However, in some sensitive areas, such as machinery condition assessment, the above-mentioned methods may be considered inadequate for validating the BSS algorithm performance. The reliability of the output data will affect the reliability of the diagnostic method and can directly affect the decision on whether the tested object needs to be repaired or replaced. Again, such a decision can lead to increased and unwanted machinery maintenance costs or, in the worst-case scenario, become ineffective in preventing potential damage and life-threatening situations. For that reason, in cases like this, it is desirable to extend the ICA reliability test method by any available means.

II. SPECIFICITIES IN SEPARATING SIGNALS RELATED TO OLTC DIVERTER SWITCH OPERATION

The focus of this paper is on the extraction of the audio signal produced by the OLTC diverter switch operation, which has been proved to be the carrier of the useful diagnostic material [15]. In the previous paper on this topic [16], one of the possible testing method, proposed is recording the OLTC audio fingerprints on a completely de-energized transformer in a quiet and isolated environment and the usage of these records as a reference for comparison with the estimates derived from applying the FastICA algorithm to the signal mixtures recorded on the active transformer. However, the problem with the proposed method is that the most active transformers are placed outside and it would be very hard to obtain satisfying conditions for recording the referent signals that could be used for ICA performance testing. On the other hand, referent signals taken from the newly produced transformers in the laboratory/factory environment do not necessarily need to coincide with the audio signals taken on the already installed OLTC of the same type, since again these records can be affected by many factors, including their age, number of operations or relative position to different rigid structures (such as walls or other machinery). Even in cases when the above would not be true, the absence of the adequate database with the referent audio fingerprints for different OLTC types would still present a problem. For that reason, another method for the verification of ICA algorithm performance is proposed here. Namely, the OLTC audio fingerprint interesting for analysis for diagnostic purposes represents a characteristic non-stationary signal that appears in a short time interval and afterward goes completely silent. Figure 1 shows a typical OLTC diverter switch audio fingerprint recorded on the de-energized transformer placed in a relatively quiet and isolated environment.

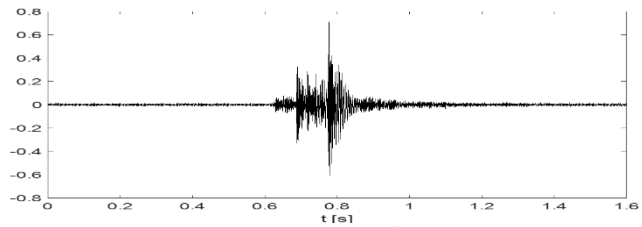

Figure 1 Typical OLTC audio fingerprint

When the transformer is energized, the OLTC audio fingerprint becomes "polluted" with the different sound signals produced by the transformer or nearby machinery. To confirm the above, several microphones were installed near the OLTC of the energized transformer. Several audio recordings, each corresponding with one OLTC TAP transition were captured by the multi-channel Tascam DR-680 field audio recorder. The OLTC was controlled manually by the system operator. A special permit issued by the electric utility was needed to perform such a test. Figure 2 shows the transformer test site, while Figure 3 shows the recorded signal mixtures.

Figure 2 Transformer test site

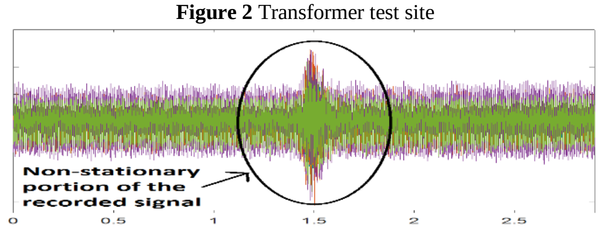

Figure 3 Audio signal mixture recorded on the active transformer

By analyzing the recorded signal mixtures, one can easily spot a portion of the signal that can be related to the OLTC diverter switch operation. Under the assumption that no new audio sources are activated during this short time interval, the recorded audio mixture can be divided into active and non-active OLTC diverter switch zones.

The basic idea is to model the part of the signal mixture where the OLTC diverter switch is not active and to use this modeled signal as a reference for testing the performance of the ICA algorithm. It should be noted that such a reference could also be used for a semi-blind source separation algorithm (such as constrained independent components analysis – CICA [17]). However, one should be careful when addressing the signal mixture this way, since the assumption regarding the new audio sources does not have to be satisfied always. A typical example of the random sound source that can be encountered in the test field is a sound produced by nearby birds. However, under the given assumption, the output of the signal model can help not only to verify the reliability of ICA results but also to select the appropriate parameters for the ICA algorithm (such as the number of input signals, time frame, nonlinearity, fine-tuning, selected approach, etc.). In this case, a non-linear least squares curve fitting method was used to model the surrounding audio signal mixture and also for the extraction of the referent signal.

III. TIME-FREQUENCY ANALYSIS OF THE RECORDED AUDIO SIGNAL MIXTURE

It has already been noted that one portion of the recorded signal mixture expresses a high non-stationary character. For that reason, a Wavelet-based approach was selected as a signal analysis method. Discrete Wavelet Transform (DWT) is based on the discretization of the dilation or scale (a) and translation (b) parameters introduced by the continuous wavelet transform (CWT), which for a finite-energy signal s(t) is defined as the integral of a signal s(t) multiplied by the scaled and shifted versions of a carrier wavelet function [18]:

$$W(a,b) = \int_R s(t)\frac{1}{\sqrt{a}}\psi^*\left(\frac{t-b}{a}\right)dt, \qquad a \in R^+, b \in R$$

where a and b represent scaling and translation parameters, respectively.

In its discrete form, the dilation parameter is usually substituted by the dyadic scale 2^m, m ∈ Z, m > 0, while the translation parameter b is represented by $n \cdot 2^m$, where the variable n now defines the time shift [19]:

$$\psi_n^m(t) = 2^{\frac{m}{2}}\psi(2^m t - n)$$

This transformation is often based on a series of interconnected low-pass filters that decompose signals into a series of low frequency approximating and high-frequency detail coefficients. The method is known as multiresolution analysis and the transformation is represented by:

$$DFT\ s(t) = \sum_{j=-\infty}^{j}\sum_{n} d_j[n] + \sum_{n} a_j[n]\varphi_{jn}, n \in \boldsymbol{Z}$$

Here, using DWT the recorded signals were decomposed at level 8, and the Sym2 mother wavelet function was intuitively selected to perform this decomposition. Figure 4 shows one of the decomposed signal mixtures.

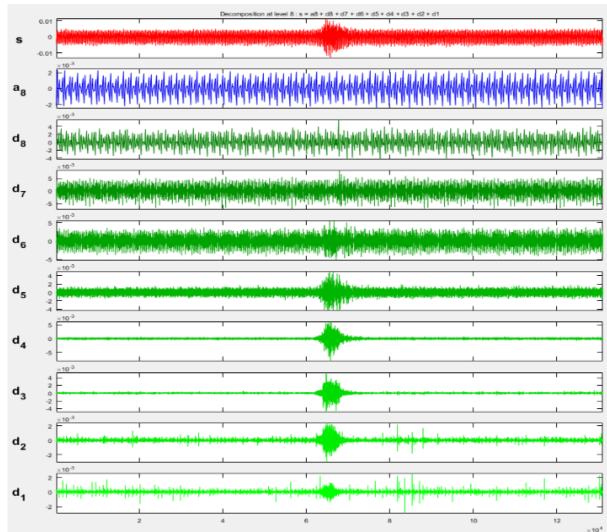

Figure 4 Signal decomposition at level 8

Analysis of the approximation and the detail coefficients shows that the signal overlap is most evident in d5-d7 (lower frequency section) and that some high-frequency noise is presented over the entire analyzed interval, which is most evident in high-frequency detail coefficients d1.

IV. IDENTIFICATION OF THE INTERESTING SIGNAL FRAMES AND EXTRACTION OF THE REFERENT OLTC FINGERPRINT

Further analysis required separation of the stationary and non-stationary signal parts (time frames which can be related to the active and non-active OLTC diverter switch operation). As it is always useful to define the procedure that is going to perform the given task automatically, a simple method for separating the two zones is described here: first, the first derivative with respect to the time step n of the signal was calculated over the entire analyzed time interval. Figure 5 shows the resulting signal.

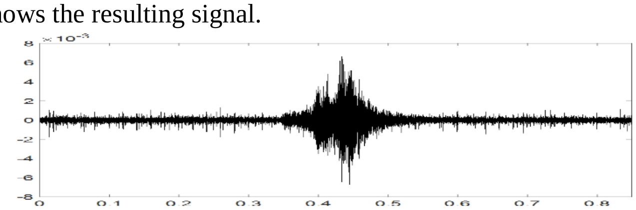

Figure 5 First derivative of the recorded signal mixture

The resulting signal, that contains $M \epsilon N$ samples, was now buffered into the $N \epsilon N$ no-overlapping data segments (frames), each containing n=M/N samples. In case the signal length is not divisible by the number of buffers, the last frame is zero-padded. For each frame, the mean and variance are calculated, according to:

$$mean_m = \frac{1}{n}\sum_{i=m*n}^{(m+1)*n} s_i$$

$$var_m = \frac{1}{n} \sum_{i=m*n}^{(m+1)*n} (s_i - mean_m)^2$$

where $m = 1,2,\ldots,M$.

The basic idea is to observe the absolute value of the difference between mean and variance over the entire time interval, which is expected to change as the stationarity of the signal is increasing/decreasing. Figure 6 shows the resulting diagram obtained by the described procedure, with selected M=100.

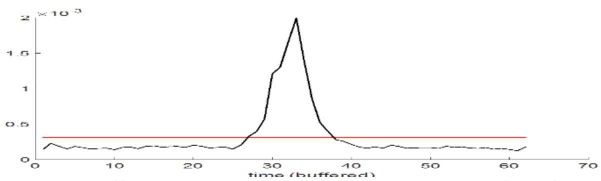

Figure 6 The difference between mean and variance in the defined frames

Now, with the proper selection of the threshold, it is easy to identify the targeted signal frames. Here, a threshold is selected according to:

$$TH = \min(d_{mv}) + 0.1 * (\max(d_{mv}) - \min(d_{mv}))$$

where d_{mv} is the signal shown in Figure 6.

Signal d_{mv} is now divided into three frames: frame T (that represents the Targeted active OLTC signal frame) and frames S1 and S2 (that represent signal intervals related to the surrounding interfering sounds). The idea is to use signal portions in the non-active OLTC time frames as a prediction data set to predict the signal values in the frame T where the OLTC audio source is active. The predicted signal values can then be used for extraction of the OLTC audio fingerprint.

Samples from any of the frames S1 or S2 can be used in the non-linear curve fitting process. However, the selection criterion here is based on the number of samples. The zone that contains more samples is selected as the one for the further analysis. A new data set $s_n(n)$, n=1,2,...,N is now used as the input data for curve fitting. A targeted curve is represented as the Fourier series model, as follows:

$$\widehat{s_n} = a_0 + \sum_{i=1}^{m} a_i * \cos(wn) + b_i * \sin(wn)$$

A non-linear least squares curve fitting method was used to fit sinusoidal curve $\widehat{s_n}$ to the given data set$\{s_n\}$. The goal is to estimate set of model parameters $\theta_i = \{a_0, a_i, b_i, w\}, i = \overline{1, m}$, by minimizing last square (LS) error criterion [20]:

$$J = (s_n - \widehat{s_n}(\theta))^T (s_n - \widehat{s_n}(\theta))$$

As the LS error, in this case, is highly non-linear, the implementation of the Levenberg-Marquardt algorithm in Matlab was used to solve the given problem. After several initial attempts, it was concluded that the method modeled the frequency content above 100 Hz quite well. Under a reasonable assumption (author's note) that the frequency content below 100 Hz is not the carrier of the useful diagnostic material, it was concluded that high pass digital filter (HPF), with selected cut-off frequency of 100 Hz, and 48dB slope, can be used to remove the low frequency harmonics. Figure 7 (up) shows the original signal samples and the estimate over the entire interval S1, while the residual plot is shown in Figure 7 (down).

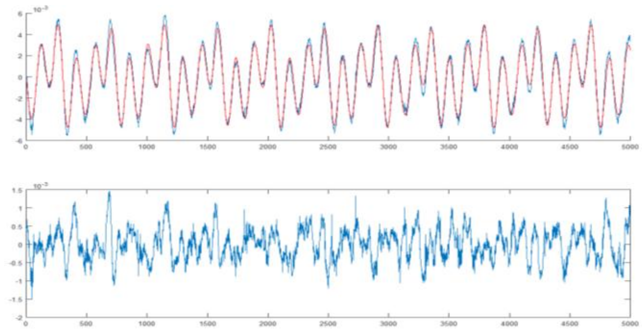

Figure 6 Original signal, signal estimate (up) and the residuals (down)

After filtering, the obtained R-square value, for the presented case, was over 0.95, which practically means that the estimated curve fits explains over 95% of the total variation in the data about the average. The resulting signal $\widehat{s_n}$ was now used for the extraction of the referent OLTC fingerprint, through the procedure graphically described in Figure 7.

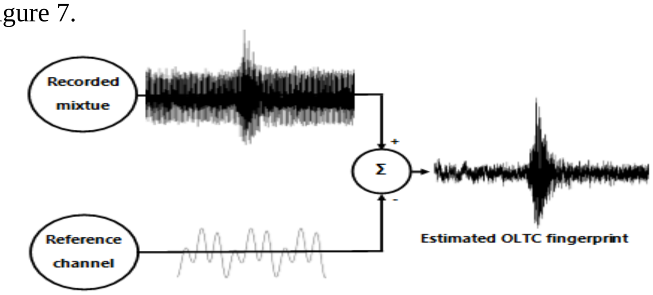

Figure 7 OLTC fingerprint extraction procedure

V. Testing performance of different ICA algorithms on signals recorded on the active transformer

As previously noted, a microphone array, consisting of six condenser microphones, placed at a distance of some 20 cm from each other, was used to simultaneously record audio signal mixtures during each OLTC TAP operation on a YNa0(d5) transformer. After initial signal analysis, it was concluded that the record captured by the first microphone quite differs from the other five signals. For that reason, this record is labeled as unreliable and disregarded for the further analysis. The remaining five records were used as input signals for the different ICA algorithms.

TABLE I: CORRELATION OF THE REFERENT OLTC FINGERPRINT AND THE TARGETED ICA ESTIMATE

	TAP1: 1-UP		TAP2: 1-DOWN		TAP3: 1-DOWN		TAP4: 1-UP		AVERAGE 4 TAPS	
	r_p	r_S	r_p	r_S	r_p	r_S	r_p	r_S	r_p	r_S
INITIAL CORRELATION	0,4939	0,5416	0,4067	0,4760	0,3702	0,4261	0,4037	0,3815	0,4186	0,4563
FPICA	0,7073	0,7554	0,6892	0,7330	0,5985	0,6561	0,6391	0,6944	0,6585	0,7097
POWERICA	0,5760	0,6092	0,7297	0,7192	0,674	0,6967	0,7663	0,7817	0,6865	0,7017
EFICA	0,6583	0,6948	0,6875	0,7289	0,5804	0,6208	0,5246	0,5334	0,6127	0,6445
NG-FICA	0,6795	0,7302	0,6808	0,7005	0,667	0,6857	0,7599	0,7693	0,6968	0,7214
THINICA	0,6577	0,7218	0,6811	0,7287	0,5914	0,6301	0,6270	0,6660	0,6393	0,6866
ERICA	0,6111	0,6445	0,6945	0,7188	0,5394	0,5778	0,5246	0,5334	0,5924	0,6186
UNICA	0,6234	0,6517	0,6941	0,7134	0,5504	0,5877	0,5254	0,5309	0,5983	0,6209

The method used for testing the performance of different ICA algorithms for extraction of the OLTC diverter switch audio fingerprint can be described as follows:

(1) Apply digital filter, with selected 100 Hz cut-off frequency and 48 dB slope, to all captured signal mixtures $\{s_1, s_2, \dots, s_n\}$. Record the filtered signals $\{s_{1f}, s_{2f}, \dots, s_{nf}\}$.

(2) Find the signal mixture $s_{fc}\ from\ \{s_{1f}, s_{2f}, \dots, s_{nf}\}$ that is mostly correlated with others. Use this signal as an input for the extraction procedure of the referent OLTC fingerprint (as described in IV). Record the referent OLTC fingerprint s_{ref}.

(3) Apply different ICA algorithms to all signal mixtures $\{s_{1f}, s_{2f}, \dots, s_{nf}\}$. Use the Monte Carlo (MC) option to execute 100 trials for the selected ICA algorithm with a randomly generated matrix. Record mean values of MC ICA estimates (independent components - IC's) as the new data set $\{s_{IC1}, s_{IC2}, \dots, s_{ICn}\}$

(4) Isolate frame T (see IV) from the referent OLTC s_{ref} and the obtained independent components $\{s_{IC1}, s_{IC2}, \dots, s_{ICn}\}$. Record the new data set s_{refT}, $\{s_{IC1T}, s_{IC2T}, \dots, s_{ICnT}\}$.

(5) Find root-mean-square (RMS) envelopes for each signal in the defined T frame. Use a window with a length of 20 samples.

(6) Find both Pearson and Spearman correlation coefficients between the RMS envelope of the referent OLTC fingerprint and the envelopes of the independent components, according to [21]:

$$\text{Pearson: } r_p(X,Y) = \frac{\sum_{i=1}^{n}(x_i-\bar{X})(y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{X})^2(y_i-\bar{Y})^2}}$$

where $\bar{X}$ and $\bar{Y}$ represent sample means of $\{x_i\}$ and $\{y_i\}$.

$$\text{Spearman: } r_s(X,Y) = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)}$$

where d_i, i=1,2,…,n represent differences in the ranks of x_i and y_i $(d_i = R(x_i) - R(y_i))$. Actually, it can be stated that the Spearman correlation coefficient represents the Pearson correlation coefficient applied to the ranks R.

(7) Find the maximum Pearson and Spearman correlation coefficient between the referent signal and the different ICA estimates. This value represents the correlation coefficient for the targeted estimate. Use these values to compare the performance of different ICA algorithms.

The described procedure was conducted on 4 different sets of records that correspond to 4 different TAP transitions (1-up, 1-down, 1-down, and 1-up). Table I shows the obtained results. The results indicate that, in average, FPICA, POWERICA, and NF-FICA had had the best performance (almost 0.7 average value of r_p, and even over 0.7 for r_s, which suggests strong linear correlation). On the other hand, the obtained values of correlation coefficients are the lowest for ERICA and UNICA.

The described procedure can also be used to optimize the set of input parameters for the selected ICA algorithm. For instance, for the selected FPICA algorithm it is desirable to determine which non-linearity function is the most suitable for a given task. For that reason, the described procedure was repeated on the signals recorded during OLTC tap transition TAP4: 1-UP, with the different selected non-linearity functions (Hyperbolic tangent, Gauss, Cubic, Opt. of cum. order 5 and order 6). Figure 8 shows the obtained r_p and r_s values for each case.

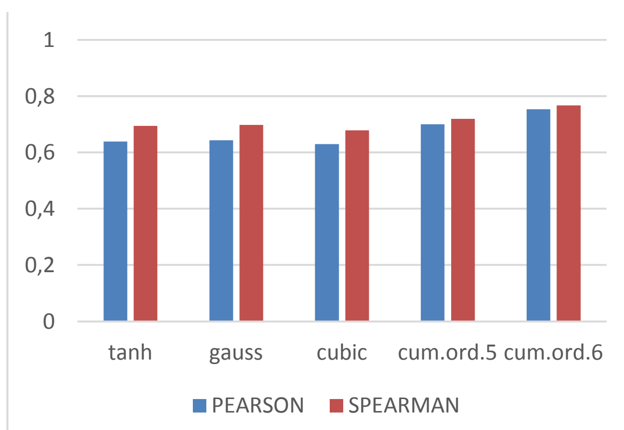

Figure 8 FPICA, different non-linearity functions

The obtained results show that the highest correlation is obtained when using Opt. of cum. order 6 as a nonlinearity function for FPICA BSS algorithm.

VI. CONCLUSION

In audio-based machinery diagnostics, Blind Source Separation is mostly used for extraction of the audio signal, which is considered to be the carrier of the useful diagnostic material, from the audio mixture simultaneously formed by the targeted source and different “interfering” audio sources. However, in such sensitive areas, the inability to determine the reliability of the resulting independent components (signals), leads to uncertainties that could also have a negative impact on decision-making processes. For that reason, any additional confirmation that yields a better understanding of BSS algorithm capabilities and the issues that may arise from using this method in solving audio-based diagnostic problems is desirable. The fact that the targeted OLTC audio fingerprint usually represents a highly non-stationary signal that appears only in a certain period when compared to the interferences in OLTC audio-based diagnostics, is used in this paper for developing the method for the extraction of the referent OLTC audio fingerprint. The developed method is based on the simple modeling approach. This signal was used as a reference for testing the performance of various ICA algorithms. The method was tested on the audio signals recorded during OLTC operation on the active YNa0(d5) transformer. The obtained results indicate that, on average, ICA-based Blind Source Separation algorithms FPICA, POWERICA, and NF-FICA had the best performance. The described procedure can also be used to optimize the set of input parameters for the selected ICA algorithm. The method could also be improved. For instance, by using a different modeling approach, it is probably possible to make a better signal prediction, and thus improve the "quality" of the reference OLTC print. This can be seen as a future work proposal.

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REFERENCES

[1] P. Comon, C. Jutte, "Handbook of Blind Source Separation", Academic Press, 22nd February 2010, eBook ISBN: 9780080884943, Hardcover ISBN: 9780123747266

[2] A. Cichocki, S. Amari, K. Siwek, T. Tanaka , Anh Huy Phan et al., "ICALAB Toolboxes", http://www.bsp.brain.riken.jp/ICALAB

[3] A. Cichocki, S. Amari, "Adaptive Blind Signal and Image Processing: Learning Algorithms and Applications", Wiley, 2003, DOI:10.1002/0470845899

[4] A. Hyvarinen, "A family of fixed-point algorithms for independent component analysis," 1997 IEEE International Conference on Acoustics, Speech, and Signal Processing, Munich, 1997, pp. 3917-3920 vol.5.

[5] S. Ding, "Independent Component Analysis without Predetermined Learning Parameters," The Sixth IEEE International Conference on Computer and Information Technology (CIT'06), Seoul, 2006, pp. 135-135.

[6] Z. Koldovsky, P. Tichavsky and E. Oja, "Efficient Variant of Algorithm FastICA for Independent Component Analysis Attaining the CramÉr-Rao Lower Bound," in IEEE Transactions on Neural Networks, vol. 17, no. 5, pp. 1265-1277, Sept. 2006.

[7] S. Choi, A. Cichocki and S. Amari, "Flexible independent component analysis," Neural Networks for Signal Processing VIII. Proceedings of the 1998 IEEE Signal Processing Society Workshop (Cat. No.98TH8378), Cambridge, 1998, pp. 83-92.

[8] S. Cruces, A. Cichocki, "Combining blind source extraction with joint approximate diagonalization: Thin Algorithms for ICA", Proc. of the Fourth Symposium on Independent Component Analysis and Blind Signal Separation, Japan, pp. 463-469, 2003.

[9] S. Cruces, L. Castedo, A. Cichocki, "Robust blind source separation algorithms using cumulants", Neurocomputing, vol. 49, pp. 87-117, 2002.

[10] S. Cruces, A. Cichocki, L. Castedo, "Blind Source Extraction in Gaussian Noise", In proceedings of the 2nd International Workshop on Independent Component Analysis and Blind Signal Separation (ICA'2000), pp. 63-68, Helsinki, Finland, June 2000.

[11] J. Himberg and A. Hyvärinen. Icasso: "software for investigating the reliability of ICA estimates by clustering and visualization", In Proc. 2003 IEEE Workshop on Neural Networks for Signal Processing (NNSP2003), pp. 259-268, Toulouse, France, 2003.

[12] J. Himberg, A. Hyvärinen and F. Esposito. Validating the independent components of neuroimaging time-series via clustering and visualization. NeuroImage 22(3):1214-1222, 2004.

[13] W. Du, S. Ma, G. Fu, V. D. Calhoun and T. Adalı, "A novel approach for assessing reliability of ICA for FMRI analysis," 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Florence, 2014, pp. 2084-2088.

[14] S. Goel, A. Verma and K. Juneja, "A framework for improving misclassification rate of texture segmentation using ICA and Ant Tree clustering algorithm," International Conference on Computing, Communication & Automation, Noida, 2015, pp. 22-27.

[15] A. Secic, I. Kuzle, "Audio-based On-Load Tap Changer diagnostics: correlation of sound and vibration fingerprints", 2018 International Symposium on Industrial Electronics, 1-3 November 2018, Banja Luka, Bosnia and Herzegovina

[16] A. Secic; K. Jambrosic; I. Kuzle; "Blind Source Separation as an Extraction Tool of the Useful Diagnostic Material in On Load Tap Changer Audio Based Diagnostics", 2018 IEEE PES ISGT Europe, 21-25 October 2018, Sarajevo, Bosnia and Herzegovina

[17] W. Lu and J. C. Rajapakse, "Constrained Independent Component Analysis", Neural Information Processing Systems (NIPS), p570-576, 2000.

[18] I.Daubechies,"Ten Lectures on Wavelets", CBMS-NSF Regional Conference Series in Applied Mathematics, 1991, ISBN: 978-0-89871-274-2, eISBN: 978-1-61197-010-4

[19] Juuso T. Olkkonen, "Discrete Wavelet Transforms: Theory and Applications", Published: April 4th 2011, DOI: 10.5772/649

[20] Steven M. Kay, "Fundamentals of Statistical Signal Processing, Volume I: Estimation Theory (v. 1) 1st Edition", Prentice-Hall, Inc. Upper Saddle River, NJ, USA ©1993, ISBN:0-13-345711-7

[21] Rodgers J. L. and W. Alan Nicewander W. A. (1988) Thirteen Ways to Look at the Correlation Coefficient. The American Statistician, 42(1), 59–66