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KURTOSIS-BASED PROJECTION PURSUIT FOR SIGNAL SEPARATION OF TRADITIONAL MUSICAL INSTRUMENTS

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ABSTRACT

Signal separation is a substantial problem in digital signal processing. The objective of signal separation from a musical composition is to decompose the composition into signals of individual musical instruments. One method that can be used is Projection Pursuit (PP) that similar with Independent Component Analysis (ICA). PP can determine source signals by projecting the data to find the most non-Gaussian distribution. In this paper we propose a method based on kurtosis as a criteria to determine non-Gaussianity. We use Mean Square Error (MSE) and Signal-to-Noise Ratio (SNR) to evaluate the accuracy of signal separation. We conducted an experiment on a synthetic and real signal mixture of traditional musical instruments i.e. Javanese Gamelan. The result showed that the minimum value of MSE for separation signal using Kurtosis-based PP (K-PP) is 1.02×10^{-5} lower than FastICA and PP. Meanwhile, the maximum value of SNR with the proposed method is 42.13 dB higher than the others.

Keywords: *Kurtosis, Projection Pursuit (PP), Independent Component Analysis (ICA), Non-Gaussian, Separation*

1. INTRODUCTION

Music is a universal language that someone can enjoy it without understanding the words of the song. As well as gamelan, one of the traditional music of Indonesia that has been known to the world [1]. Gamelan consists of many instruments that played together like an orchestra. However the playing of gamelan has no conductor who directs the strains of the song. Instead of an instrument may function as the leader direct the playing of other instruments. Thus a gamelan player must be able to listen clearly the sound produced by the instrument that serves as a conductor.

This issue in digital signal processing is a problem of signal separation. The goal of signal separation is to determine the components signal that construct mixed signals [2]. Separation of musical instruments signal is very useful in instrument sound recognition, remixing musical processing, audio coding, and signal analyzer supporting instruments [3].

Music is composed of a number of instruments sounds to produce a harmonious sound that comfortable to hear [4]. This means that the music is a mixture of several sound signals generated from instruments. If we want to know the sound produced by a particular instrument, we must focus our hearing on that tones. This is an attempt to get the separation of signals that arrange the mixture.

One popular method to separate signals is Independent Component Analysis (ICA). ICA has two principles i.e. independent statistically and non-Gaussian distribution maximally [2]. The principle of maximal non-Gaussianity is similar to find a projection with maximal non-Gaussian distribution in Projection Pursuit (PP). In other words, an independent component can be found by a projection pursuit direction. We propose PP based on kurtosis as a criteria to determine non-Gaussianity. This method that we called Kurtosis-based PP (K-PP) will seek the most appropriate projection to obtain a component of mixed signals. We would rotate the data to obtain projection that has a non-Gaussian distribution maximally.

In this paper we perform separation tests on gamelan signals instruments, in particular Javanese Gamelan. Gamelan consists of 5 groups, i.e., *Gongan* (Gong Ageng, Gong Suwukan, Kempul, Kenong, Kethuk, Kempyang), *Balungan* (Saron Demung, Saron Bonang, Saron Penerus, Slenthem), *Bonang* (Bonang Barung, Bonang Penerus), *Panerusan* (Rebab, Gender, Gambang, Siter, Suling) and *Kendhang* (Kendhang Ageng, Kendhang Ciblon, Kendhang Sabet, Ketipung) [5]. An example of gamelan instruments can be seen on Figure. 1.

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Figure 1: A Set of Gamelan

The rest of this paper is organized as follows. Section 2 explains the related and recent works. Section 3 formulates the problem of separating instrument signals. We describe our proposed method in Section 4. In Section 5, experiments were conducted and Section 6 concluded them.

2. RELATED WORKS

2.1 The Musical Signal Separation

In musical issues, the problem of signal separation is obtaining the individual track of each instrument [3] and the voice of the singer if there exist. The fundamental principle is knowing how many sources (m instruments and voices) that make n mixture signals. Then estimating the $n \times m$ mixing matrix to get the sources. It is a usual technique for instantaneous mixtures, while for convolutive mixtures it is more complicated.

There are some approaches to solve the musical signal separation such as ICA. Vannroose subtract music background using ICA [6]. Puolivali et. al. use semi-blind ICA to decompose continuous music [7]. Chien and Hsieh demonstrate that Convex divergence ICA (C-ICA) can separate mixture of speech and music signals [8].

Another researches take some characteristics of music or acoustic signal to separate musical instruments signal. Vincent use time-frequency source prior to separate stereo musical mixtures [9]. Li, Wodruff and Wang use pitch and amplitudo modulation to separate monaural musical [10]. Gunel et.al. separate instrument and speech convolutive mixtures based on intensity vector [11].

Degenerate Unmixing Estimation Technique (DUET) with time-frequency scheme used by Wang [12], Sinith [13] and Misssaoui [14]. While Virtanen [15], Ozerov [16], and Kitamura et.al [17] apply Nonnegative Matrix Factorization (NMF) for musical source separation. We did not use both because our data represented in time-domain and not nonnegative matrixes.

2.2 The Projection Pursuit

Projection Pursuit (PP) is a statistical method that concern with "interesting" projections of a dimensional data [18]. PP find such projections that appropriate with nonparametric fitting or data-analytic purposes.

PP was applied in many problems such as exploration of multivariate data [19], feature reduction of high dimensional data [20], feature extraction and classification [21], [22]. PP also implemented for mixture density estimation [23]. PP approach can be used for robust linear discriminant analysis [24] and optimization of kurtosis [25].

Sarajedini and Chau [26] adapted Exploratory Projection Pursuit for Blind Signal Separation (BSS) using associated projection pursuit index. The famous paper (more than 5000 citations) of Hyvarinen [2] used ICA and projection pursuit approach. Sergio, Cichocki, and Amari [27] comparing some algorithms include PP for blind instantaneous separation on image data. Dutta, Gupta, and Pathak [28] claimed that PP is efficient than DUET for underdetermined ($m > n$) BSS of instantaneous audio mixtures.

Recently, Yang et.al. [2013] presented a PP based method for blind separation of nonnegative sources. Their proposed method estimate the mixing matrix column by column to trace the projections. They put on their method on image data that only contain positive numbers or zero. Meanwhile, an acoustic signal (including musical instruments signal) in time-domain is not a nonnegative matrix, so we can not use this method to separate them. It is a challenge for us to modify PP that can be used for any matrixes. Especially for separating instruments gamelan signals which acted as a conductor on a gamelan playing. Moreover the instrument conductor could be vary throughout the gamelan performance.

2.3 Data Preparation

Our data is about gamelan instruments signals. First of all, we studied about the characteristics of gamelan. Each instruments of a set of gamelan has a specific function and produced different sound among others. We focused on Balungan group (Demung, Saron, and Peking) that served as melody in gamelan playing. Saron has an octave higher than Demung, but lower than Peking. The rule of Balungan playing is beating the same tone from Demung, Saron, and Peking simultaneously.

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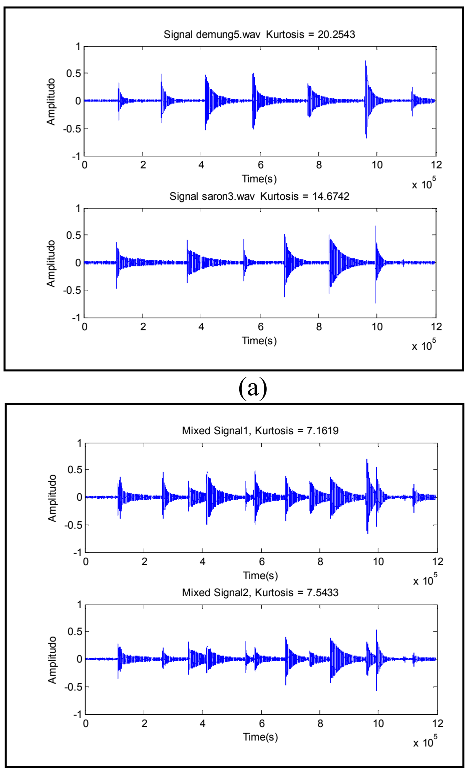
We have been doing research on testing Gaussian distribution for each tone of Demung, Saron, and Peking. We use kurtosis for measuring Gaussianity and the result show that every tone of them has non-Gaussian distribution [30]. Furthermore, we count the kurtosis of the mixture data. According to our experiments, the kurtosis value of mixed data is always smaller than the kurtosis value of its components. It means that the mixed data tend to be more Gaussian than the sources. As an example, Figure. 2(a) show the sources signals and Figure. 2(b) present the mixture of data both with the value of kurtosis.



(a)

(b)

Figure. 2. Signals And The Value Of Kurtosis (A) Source Data (B) Mixed Data

Unfortunately, we got some troubles to check the independence from the source data. We have tried some methods, Chi-Square and Least-Square, to determine the independent statistically between two components, but the result show an inconclusive results. As a solution, we make an assumption that the components were statistically independent if we want to use ICA for separating instruments signals of gamelan. Otherwise, we must check the independence between the estimated separated signals [31].

These facts lead us to use Projection Pursuit (PP) that based on the Gaussianity of the components. PP seek the projection that has maximal non-Gaussian distribution as an component.

3. PROBLEM FORMULATION

A signal can be presented as a vector so that a mixture of n signals with m samples can be presented as $n \times m$ matrix. The goal of signal separation is to estimate the mixing matrix in order to get the source signals. Suppose $\boldsymbol{X}$ is $n \times m$ non-singular matrix that represents the mixture and $\boldsymbol{A}$ is the mixing matrix, the source signals $\boldsymbol{S}$ can be formulated as in (1).

$$\boldsymbol{X} = \boldsymbol{AS} \quad (1)$$

The goal is estimating the source signal $\boldsymbol{S} = (s_1, s_2, \dots, s_n)^T$ up to the term defined. To obtain the source signal, we must estimate the mixing matrix $\boldsymbol{A}$ to be nonsingular so we can find the inverse of matrix $\boldsymbol{A}$ and calculate the source matrix $\boldsymbol{S}$ using Eq. (2).

$$\boldsymbol{S} = \boldsymbol{A}^{-1}\boldsymbol{X} \quad (2)$$

The mixing matrix $\boldsymbol{A}$ is unknown so it needs an approach to separate signals. The conventional method is Independent Component Analysis (ICA) that depends on independence and non-Gaussian distribution [2]. One of ICA algorithm is FastICA that use negentropy as described in Eq. (3).

$$J(x) = \left[E\{G(x)\} - E\{G(v)\}\right]^2 \quad (3)$$

In Eq. (3), E is expectation and v is normal random variable N(0,1), while $G(x)$ could be $G(x) = \frac{1}{\alpha}\log\cosh(\alpha x)$ or $G(x) = -\exp\left(\frac{x^2}{2}\right)$ where $1 \le \alpha \le 2$.

Our research is about separating signals of gamelan instruments. Each instrument produces monophonic audio signals such that every tone has a fundamental frequency [32]. Some of them have the same fundamental frequency, some do not. We had worked on separating of a gamelan instrument signals that have different fundamental frequency [33]. In this paper we conduct to separate gamelan instruments signals that have similar fundamental frequency.

4. PROPOSED METHOD

Projection is a linear transformation from a vector space to itself or another vector space but it still keeps the data information. Projection of data can visualize its distribution. Projection pursuit involves to extract non-Gaussian components in general setting [34]. In separating signal, our goal is finding a projection that show the separation of mixture data. According to Central Limit Theorem

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(CLT) that mixture data tend to be Gaussian while the components tend to be non-Gaussian, we seek to find the most non-Gaussian direction in mixture data.

We can measure the non-Gaussianity of data using kurtosis as described in (4).

$$\beta = \frac{E\left[s - E[s]^4\right]}{\left(E\left[\left(s - E[s]\right)^2\right]\right)^2} - 3 \qquad (4)$$

$E(s)$ is the expected value of the quantity s. The data with Gaussian distribution will has value of kurtosis $\beta = 0$. The negative kurtosis will be sub-Gaussian while positive kurtosis will be super-Gaussian. Our goal is to find projection of mixture data that has value of kurtosis farthest from zero.

Our proposed method is represented in Figure. 3. We assume that the source data consist of n mixed signals that represented in matrix $\mathbf{X} = (x_1, x_2, \ldots, x_n)^T$. First, we do centering to get zero mean and unity variance as in (5).

$$\bar{x}_i = x_i - \frac{1}{n}\sum_{j=1}^{n} x_j \qquad (5)$$

Then we do sphering or pre-whitening using Eq. (6).

$$\tilde{x}_i = \left(\frac{1}{n}\sum_{i=1}^{n} \bar{x}_i \bar{x}_i^{T}\right)^{-\frac{1}{2}} \bar{x}_i \qquad (6)$$

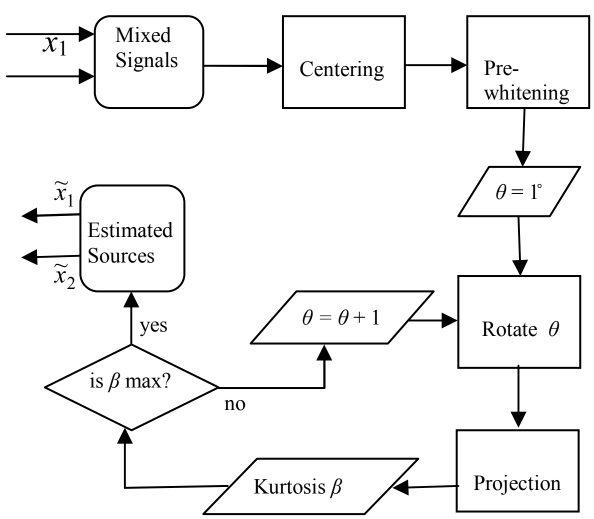

Figure. 3. Blok Diagram Of K-PP

To find interesting projection, we use rotation on $\tilde{X} = \left(\tilde{x}_1 | \tilde{x}_2 | \cdots | \tilde{x}_n\right)$ with matrix $\mathbf{R}$ for degree θ as describe in (7).

$$\mathbf{R} = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \qquad (7)$$

We choose θ to get estimated source components based on orthogonal projection. First we try $\theta = 1°$ to rotate the data and then project it orthogonally. We calculate β as the value of kurtosis for every component. If β is not maximum then the data rotate again with increased θ. It is done several times to obtain β maximum.

When the value of kurtosis is maximum it indicates that the component is maximally separated. Due to the process to separate mixed signals is depend on the angle of rotation so we called our proposed method as Kurtosis-based Projection Pursuit (K-PP).

5. EXPERIMENTAL RESULTS

5.1 Performance Evaluation of K-PP

Our research is about separating instruments signals of traditional music from Indonesia, gamelan. We recorded the sounds of gamelan instruments individually and then mixed them using a random matrix to become instantaneous mixtures. We also recorded two instruments together to get recorded mixture.

Gamelan consists of five group from several different instruments. There are Bonang and Saron that have the same range of fundamental frequency. We arrange data from Bonang and Saron instrument signals.

According to the method of K-PP that has angle as parameter, we tried to rotate data from 0 until 90 degree. Then we use orthogonal projection to get the estimated component based on kurtosis value. The higher or the lower of kurtosis value is the most non-Gaussian of the data.

First of all, we try to separate synthetic signal of gamelan. We generate two different synthetic signal of gamelan as formulated in Eq. (8), (9), and (10) [35].

The Synthetic Demung:

$$sr_d = A\sin\left(2\pi\left(\frac{f}{fs}\right)x + \theta\right)0.8223e^{-1.194\times10^{-5}x} \qquad (8)$$

The Synthetic Saron:

$$sr_s = A\sin\left(2\pi\left(\frac{f}{fs}\right)x + \theta\right)0.7693e^{-1.08\times10^{-5}x} \qquad (9)$$

The Synthetic Peking:

$$sr_p = A\sin\left(2\pi\left(\frac{f}{fs}\right)x + \theta\right)0.7663e^{-1.709\times10^{-5}x} \qquad (10)$$

Where sr_d, sr_s, and sr_p are synthetic signals of Demung, Saron, and Peking respectively, A is amplitudo, θ is phase, f is fundamental frequency of reference signal, fs is frequency sampling, and x is the length of data.

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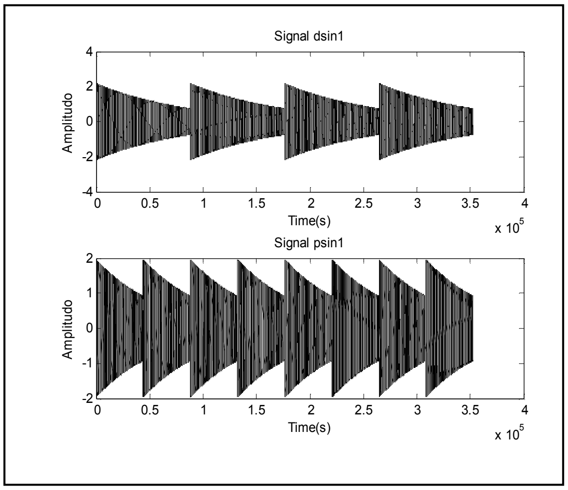

Figure. 4. Source Of Synthetic Signals

As an example, Figure. 4. shows the source signals and instantaneous mixture data. We do centering and sphering the data that shown in Figure. 5 as blue. Then we rotated and projected orthogonally to estimate the components of separation. We seek rotation that show the mixture data simetrically to the axis that shown in Figure. 5 as red.

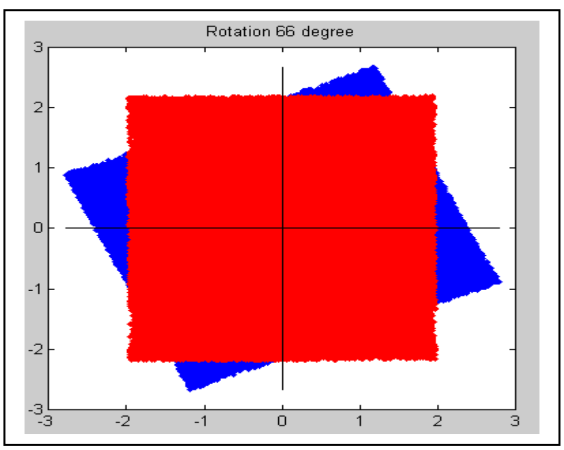

Figure. 5. Centering And Sphering (Blue), Rotating (Red)

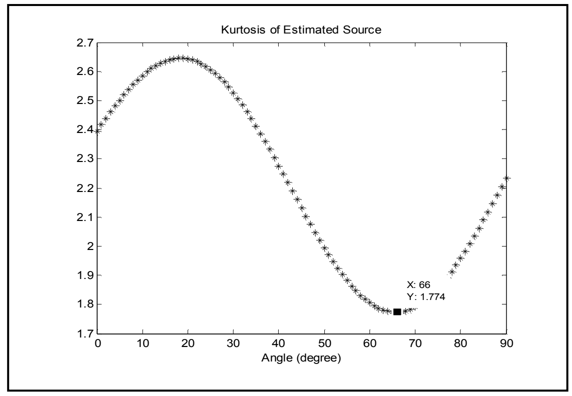

Figure. 6. The Kurtosis Value Of Estimated Source Signal

To measure the non-Gaussianity of estimated source signal, we calculate the value of kurtosis for rotation degree from 0 until 90 as depict in Figure. 6.

We calculate Mean Square Error (MSE) as in (11) to evaluate the performance of separating signal. We use Signal-to-Noise Ratio (SNR) that is described in (12) to compare the source signal and the result of separating as estimated source signal

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\tilde{x}_i - x_i\right)^2 \qquad (11)$$

$$SNR_{dB} = 10\log_{10}\left[\left(\frac{\tilde{x}_i}{\tilde{x}_i - x_i}\right)^2\right] \qquad (12)$$

Signal x_i is the i^{th} source signal while $\widetilde{x}_i$ is the i^{th} estimated source signal.

The value of MSE and SNR for separating instantaneous synthetic mixture for every degree are shown in Figure. 7. and Figure. 8

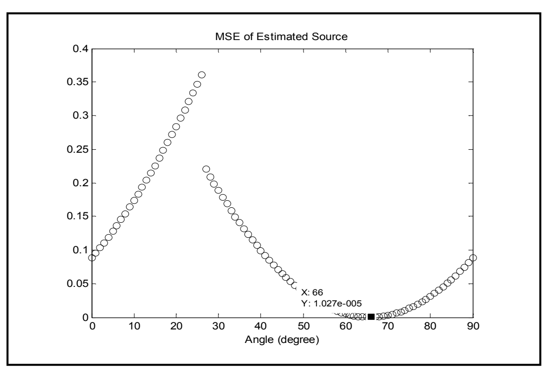

Figure. 7. The MSE Of Estimated Source Signal

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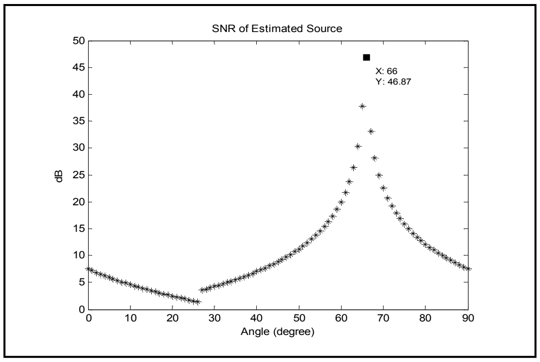

Figure. 8. The SNR Of Estimated Source Signal

From Figure. 7. until Figure. 8., we can see that the separation of instantaneous mixed synthetic gamelan signals reach optimal result on a certain degree of rotation, in this case is 66^o.

For the next experience, we work with gamelan signals that are recorded from Gamelan Elektro Budoyo in Department of Electrical Engineering, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia.

For instantaneous mixtures, we use Saron signal and Bonang signal that have close similarity in fundamental frequency. As an example, Figure. 9. shows a part of song Manyar Sewu played by Saron and Bonang.

We mixed two source signal by a random matrix and then centering and sphering that shown in Figure. 10. As blue. Then data is projecting orthogonally to separate the instantaneous mixed signal. We try to rotate the data to get optimally separation that symmetrically that shown in Figure. 10. as red.

To measure non-Gaussianity of estimated source signal, we calculate the value of kurtosis. To evaluate the performance of separation we use MSE and SNR. Some result are shown in Table I due to some degree for the angle of rotation data.

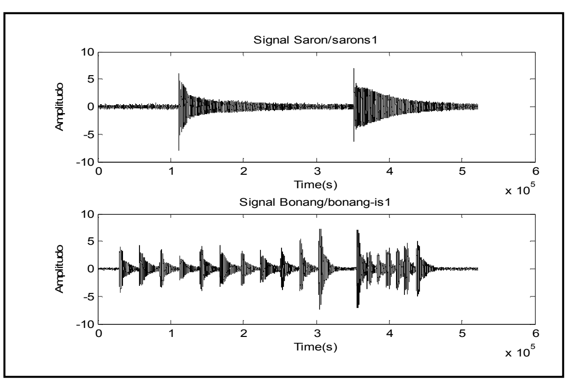

Figure. 9. Source Signals Of Saron And Bonang

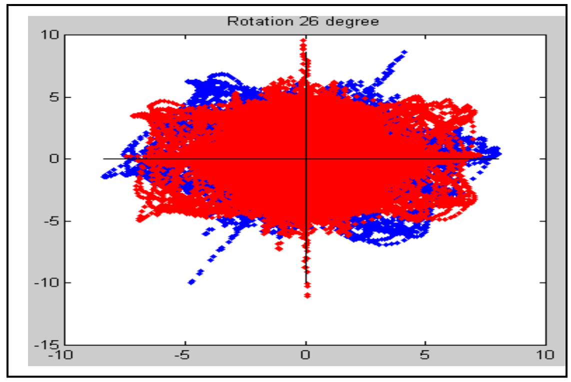

Figure. 10. Centering And Sphering (Blue), Rotating (Red)

Table I : The Result Separation Of Saron And Bonang (Instantaneous Mixture)

Angle (Degree)	Kurtosis	MSE	SNR (dB)
1	8.92094227	0.090411859	7.42743776
10	9.52906271	0.036610194	11.35367137
20	9.97985967	0.004690389	20.27760267
25	10.0542538	4.63E-05	40.33116275
27	10.0552731	3.06E-05	42.12773387
30	10.0516016	0.000319538	31.94447125
40	9.60825338	0.031627523	11.98903989
50	8.92811981	0.089665991	7.463414209
60	8.24207411	0.175364439	4.550276439
80	7.75848927	0.418564342	0.772069456
82	7.79381401	0.447312467	0.483581713
85	7.87041021	0.491686036	0.072812987
90	8.04785209	0.568676292	-0.55895949

The detail results in kurtosis value, MSE, and SNR are shown in Fig 11.

From Figure. 11. we can see that the maximum kurtosis value reached when the minimum value of MSE found and the maximum SNR met. In this case, all were happened in the same degree of rotation i.e. 27^o.

For another mixing matrix that composed instantaneous mixture it would found a certain degree of rotation that will produce the maximum kurtosis and minimum MSE also maximum SNR. In other words, our K-PP methods will found the separation of instantaneous mixture gamelan instruments signals.

The third experiment was conducted for recorded signal of two instruments that played together. We tried to play Bonang and Saron that have similar fundamental frequency. Table II shows

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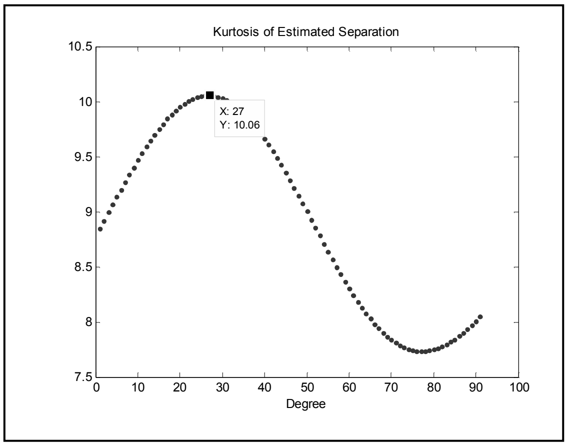
the results of separation for recorded signal of Bonang and Saron. The detail result of separation recorded mixture of Bonang and Saron are shown in Figure. 12.



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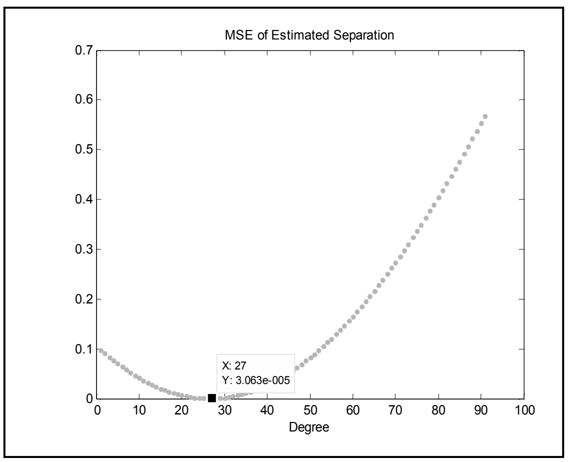

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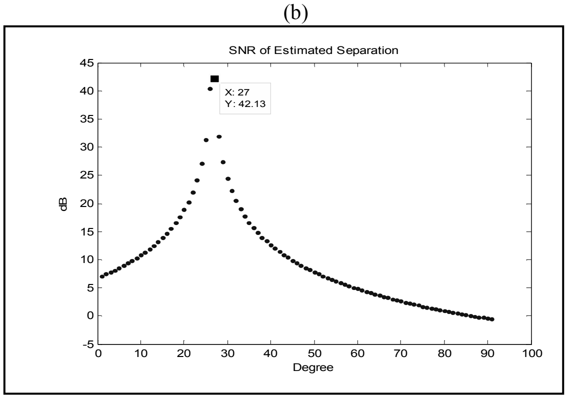
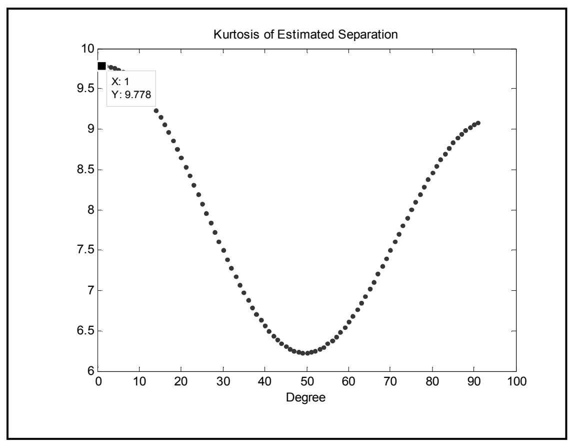


(c)

Figure. 11. The Estimated Signal Source On (A) Kurtosis, (B) MSE, And (C) SNR

Tabel II : The Result Separation of Bonang and Saron (Recorded Mixture)

Degree	Kurtosis	SNR
0	9.778122890	22.66154231
1	9.779671249	25.01090301
3	9.760205832	19.29319912
4	9.739215017	17.99942716
10	9.461864923	12.75817209
25	7.958802821	6.23978002
40	6.498811604	2.655989459
55	6.381803636	-5.682161097
65	7.110586689	-5.862731908
80	8.548665853	-6.005380188
90	9.086840684	-6.017173852



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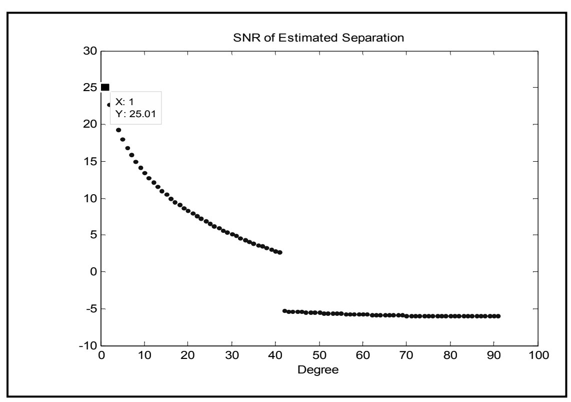

(b)

Figure. 12. The Result Of Separation Recorded Mixture On (A) Kurtosis And (B) SNR

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In Figure. 12. we can see that the maximum kurtosis value reached when SNR value is found. In this case the optimum separation happened for rotation 1^o. It looks like that the recorded data is almost separated.

5.2 The Comparison of FastICA, PP, and K-PP

We also tried to separate gamelan instruments signal use FastICA and PP in order to compare to K-PP. The experiments were performed in synthetic signals, instantaneous mixtures, and recorded signals.

To evaluate the performance of FastICA, PP and K-PP we use MSE and SNR as in Table III and Table IV.

Table III: MSE Comparison of FastICA, PP and K-PP

Type of mixed signals	MSE (Min) x 10^{-5}		
	FastICA	PP	K-PP
Synthetic	1.14	1.56	1.02
Instantaneous	5.27	6.35	3.06
Recorded	63.7	54.3	47.2

Table IV: SNR Comparison of FastICA, PP and K-PP

Type of mixed signals	SNR (Max) in dB		
	FastICA	PP	K-PP
Synthetic	43.25	38.48	46.87
Instantaneous	36.02	32.52	42.13
Recorded	21.19	22.26	25.01

6. CONCLUSIONS

We have done separation on gamelan instruments signals using K-PP with angle as parameter for orthogonal projection. The results show that each angle gave different solutions. Based on our experiments, the separation would be optimal if the representation of mixture data was in symmetrical shape. The measurement on kurtosis, MSE and SNR gives the same optimum value for separation on synthetic mixed signals, instantaneous mixtures and recorded signals.

The synthetic mixed signals have the lowest value of MSE and the higher SNR. This is makes sense because synthetic signal is simple and noise free. The opposite occur on recorded mixed signals where the mixing matrix is unknown. The FastICA is better than PP in synthetic mixed and instantaneous mixture but worse for recorded signals.

In our experiments of separation gamelan instruments signals, our proposed method (K-PP) is better than the conventional methods (FastICA or PP). However it is done on the separation of two instruments signal that need to be tested on many even all of gamelan instruments or other musical types. For future works, it should be tried on another type of projection, for example oblique projection.

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REFRENCES:

[1] J. F. Titon (General Editor), *Worlds of Music: An Introduction to The Music of The World's Peoples* Fifth Edition 2009, Schirmer Cengage Learning, 2002.

[2] A. Hyvarinen, E. Oja, "Independent Component Analysis:Algorithms and K-PPlications", *Neural Networks*, Vol. 13, No 4-5, 2000, pp. 411 - 430.

[3] M. Muller, D. P. W. Ellis, A. Klapuri, and G. Richard, "Signal Processing for Music Analysis", *IEEE Journal of Selected Topics in Signal Processing*, Vol. 5, No.6, 2011, pp. 1088-1110.

[4] J. P. Bello, L. Daudet, S. Abdallah, C. Duxbury, M. Davies, M. B. Sandler, "A Tutorial on onset Detection in Music Signals", (2005) *IEEE Transactions on Speech and Audio Processing*, Vol. 13, No. 5, 2005, pp. 1035-1047.

[5] Sumarsam, *Gamelan Cultural Interaction and Musical Development in Central Java*, The University of Chicago Press, 1992.

[6] P. Vanroose, "Blind source separation of speech and background music for improved speech recognition", *Proceeding of The 24th Symposium on Information Theory*, 2003, pp. 103–108.

[7] T. Puolivali, et. al, "Semi-Blind Independent Component Analysis of Functional Elicited by Continuous Listening to Music", *Proceeding of The IEEE International Conference on Acoustics, Speech and Signal Processing*. 2013, DOI: 10.1109 /ICASSP.2013.6637863.

[8] J-T. Chien, H-L Hsieh, "Divergence ICA for Blind Source Separation", *IEEE Transactions*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

on Audio, Speech, and Language Processing, Vol. 20, No. 1, 2012, pp. 302-313.

[9] E. Vincent, "Musical Source Separation Using Time-Frequency Source Priors", *IEEE Transactions On Audio, Speech, And Language Processing*, Vol. 14, No. 1, 2006, pp. 91-98.

[10] Y. Li, J. Woodruff, DL. Wang, "Monaural Musical Sound Separation Based on Pitch and Common Amplitudo Modulation", *IEEE Transactions On Audio, Speech, And Language Processing*, Vol. 17, No.7, 2009, pp. 1361-1371.

[11] B. Gunel, H. Hacihabiboglu, A. M. Kondoz, "Acoustic Source Separation of Convolutive Mixtures Based on Intensity Vector Statistics", *IEEE Transactions On Audio, Speech, And Language Processing*, Vol. 16, No. 4, 2008, pp. 748-756.

[12] Y. Wang, O. Yilmaz, and Z. Zhou, "Phase Aliasing Correction For Robust Blind Source Separation Using DUET", *Applied and Computational Harmonic Analysis*, Vol. 35, No. 2, 2013, pp. 341-349.

[13] M. S. Sinith, M. N. Nair, N. P. Nair, S. Parvathy, "Blind Source Separation of Musical Instrument Signals by Identification of Wavelets and Filter Bank Coefficients", *Proceedings of the Recent Advances in Intelligent Computational Systems (RAICS)*, Page: 129-133 Year of Publication: 2011 ISBN:978-1-4244-9478-1.

[14] I. Misssaoui, "Speech Separation Using DUET and Binary Masking with Temporal Smoothing in Cepstral Domain", *Proceedings of the World Congress on Computer and Information Technology (WCCIT)*, Page: 1-4 Year of Publication: 2013 ISBN:978-1-4799-0406-0.

[15] T. Virtanen, "Monaural Sound Source Separation by Nonnegative Matrix Factorization With Temporal Continuity and Sparseness Criteria", *IEEE Transactions On Audio, Speech, And Language Processing*, Vol. 15, No. 3, 2007, pp. 1066-1074.

[16] A. Ozerov, C. Fevotte, "Multichannel Nonnegative Matrix Factorization in Convolutive Mixtures for Audio Source Separation", *IEEE Transactions On Audio, Speech, And Language Processing*, Vol. 18, No. 3, 2010, pp. 550-563.

[17] D. Kitamura, H. Saruwatari, K. Shikano, K. Kondo, Y Takahashi, "Music Signal Separation by Supervised Nonnegative Matrix Factorization with Basis Deformation", *Proceedings of the 18th International Conference on Digital Signal Processing (DSP)*, Page: 1-6 Year of Publication: 2013 ISSN:1546-1874.

[18] P. J. Huber, "Projection Pursuit", *The Annals of Statistics*, Vol. 13, No. 2, 1985, pp. 435-475.

[19] D. M. Glover, and P. K. Hopke, "Exploration of multivariate chemical data by projection pursuit", (1992), *Chemometrics and Intelligent Laboratory Systems*, Vol. 16, No. 1, pp. 45-59.

[20] L. O. Jimenez, D. A. Landgrebe, "Projection Pursuit for High Dimensional Feature Reduction: Parallel and Sequential K-PProaches", *Proceedings of the International Geoscience and Remote Sensing Symposium (IGARSS'95)*, Page: 148-150 Year of Publication: 1995 ISBN: 0-7803-2567-2.

[21] Y. Zhao and C. G. Atkeson, "Implementing Projection Pursuit Learning", 1996 *IEEE Transactions on Neural Networks*, Vol. 7, No. 2, 1996, pp. 362-373.

[22] E. R. Martinez, J. Y. Goulermas, T. Mu, and J. F. Ralph, "Automatic Induction of Projection Pursuit Indices", 2010 *IEEE Transactions on Neural Networks*, Vol. 21, No. 8, 2010, pp. 1281-1295.

[23] M. Aladjem, "Projection Pursuit Mixture Density Estimation", *IEEE Transactions on Signal Processing*, Vol. 53, No. 11, 2005, pp. 4376-4383.

[24] A. M. Pires, J. A. Branco, "Projection-pursuit K-PProach to robust linear discriminant analysis", *Journal of Multivariate Analysis*, 2010, pp. 2464-2485.

[25] S. Hou, P. D. Wentzell, "Fast and simple methods for the optimization", *Analytica Chimica Acta*, 2011, pp. 1-15.

[26] A. Sarajedini, P. M. Chau, "Blind Signal Separation With A Projection Pursuit Index", *Proceeding of the 1998 IEEE International Conference on Acoustic, Speech and Signal Processing*, Page: 2125-2128 Year of Publication: 1998 ISBN: 0-7803-4428-6.

[27] S. A. Cruces-Alvares, A. Cichocki and S. Amari, From Blind Signal Extraction to Blind Instantaneous Signal Separation: Criteria, Algorithms, and Stability, *IEEE Transactions on Neural Networks*, Vol. 15, No. 4, 2004, pp. 859-873.

[28] M. K. Dutta, P. Gupta, V. K. Pathak, "An Efficient Algorithm for Undetermined Blind Source Separation of Audio Mixtures", *Proceeding of the 2009 IEEE International Conference on Advances in Recent*

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Technologies in Communication and Computing, Page: 136-140 Year of Publication: 2009 ISBN: 978-0-7695-3845-7.

[29] Z. Yang, Y. Xiang, Y. Rong, and S. Xie, "Projection-Pursuit-Based Method for Blind Separation of Nonnegative Sources", *IEEE Transactions on Neural Networks And Learning Systems*, Vol. 24, No. 1, 2013, pp. 47-59.

[30] A. Wintarti, Y. K. Suprapto, "Deteksi Independensi dan Non-Gaussian untuk Indepent Component Analysis (ICA)", *Proceeding of The 13th Seminar on Intelligent Technology and Its K-PPlications*, 2012, ISSN: 2252-8296.

[31] A. Hyvarinen, P. Ramkumar, "Testing Independent Component Patterns by Inter-subject or Inter-session Consistency", *Frontiers in Human Neuroscience,* DOI:10.3389/ fnhum.2013.00094.

[32] Y. K. Suprapto, M. Hariadi, M. H. Purnomo, "Traditional Music Sound Extraction Based on Spectral Density Model using Adaptive Cross-Correlation for Automatic Transcription", *IAENG International Journal of Computer Science*, Vol. 38, No. 2, 2011.

[33] A. Wintarti, Y. K. Suprapto, "Separation of Gamelan Instruments Signal Using ICA Based on Projection Pursuit", *Proceeding of The International Seminar on Intelligent Technology and Its K-PPlications (ISITIA)*, Page 285-290 Year of Publication 2015 DOI:10.1109/ISITIA.2015.7219993

[34] M. Sugiyama, M. Kawanabe, G. Blanchard, K-R. Muller, K-PProximating the Best Linear Unbiased Estimator of non-Gaussian Signals with Gaussian Noise, (2008) *IEICE Transactions on Information and Systems*, Vol. E91-D, No. 5, 2008, pp. 1577-1580.

[35] Y. K. Suprapto, V. E. Pradhana, "High Performance Gamelan Analyzer Using Adaptive Waveform Pattern Matching", *Journal of Theoretical and K-PPlied Information Technology*, Vol. 7, No. 1, 2015, pp. 13-22.