

An Efficient Pairwise Kurtosis Optimization Algorithm for Independent Component Analysis

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Abstract. In the framework of Independent Component Analysis (ICA), kurtosis has been used widely in designing source separation algorithms. In fact, the sum of absolute kurtosis values of all the output components is an effective objective function for separating arbitrary sources. In this paper, we propose an efficient ICA algorithm via a modified Jacobi opti-

if $\theta = \theta_0$, then $J(\theta) = J(\theta_0)$. \square

$$c = \frac{3}{4}E\{y_l^4 + y_k^4\} + \frac{3}{2}E\{y_l^2 y_k^2\} - c, \quad (1)$$

$$A = \sqrt{(E\{y_l^4 + y_k^4\} - c)^2 + (E\{y_l^3 y_k - y_k^3 y_l\})^2}, \quad (1)$$

$$B = \sqrt{(E\{y_l^4 - y_k^4\})^2 + (2E\{y_l^3 y_k + y_k^3 y_l\})^2}, \quad (1)$$

$$\alpha = \begin{cases} \arctan((E\{y_l^4 + y_k^4\} - c)/A), & \text{if } \alpha > 0, \\ \pi - \arctan((E\{y_l^4 + y_k^4\} - c)/A), & \text{else,} \end{cases} \quad (1)$$

$$\beta = \begin{cases} \arctan(E\{y_l^4 - y_k^4\}/B), & \text{if } \beta > 0, \\ \pi - \arctan(E\{y_l^4 - y_k^4\}/B), & \text{else.} \end{cases} \quad (1)$$

Let θ_0 be the value of θ that minimizes $J(\theta)$. Then, θ_0 is the value of θ that minimizes $J(\theta)$. (3).

$$\theta_0 = \begin{cases} \frac{\pi}{2} - \alpha/4, & \text{if } c \geq 0, \\ -\frac{\pi}{2} - \alpha/4, & \text{if } c < 0. \end{cases} \quad (20)$$

$$\theta_0 = \frac{\pi}{2} - \beta/2, \quad (21)$$

Let θ_0 be the value of θ that minimizes $J(\theta)$. Then, θ_0 is the value of θ that minimizes $J(\theta)$. (3).

$$E\{y_l^4\}, E\{y_k^4\}, E\{y_l^3 y_k\}, E\{y_l y_k^3\} \text{ and } E\{y_l^2 y_k^2\} \quad (22)$$

Let $\mu_{4,0}, \mu_{0,4}, \mu_{3,1}, \mu_{1,3}$ and $\mu_{2,2}$ be the fourth-order moments of y_l and y_k . Then, $E\{y_l^4\} = \mu_{4,0}$, $E\{y_k^4\} = \mu_{0,4}$, $E\{y_l^3 y_k\} = \mu_{3,1}$, $E\{y_l y_k^3\} = \mu_{1,3}$ and $E\{y_l^2 y_k^2\} = \mu_{2,2}$. (22)

Let θ_0 be the value of θ that minimizes $J(\theta)$. Then, θ_0 is the value of θ that minimizes $J(\theta)$. (3).

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The proposed algorithm is compared with the J-
 method [10] in terms of the number of iterations required to
 reach a convergence threshold of 0.002. The results are shown
 in Table 1. It can be seen that the proposed algorithm
 converges much faster than the J-method.

5 Conclusion

In this paper, a new pair-wise kurtosis optimization algorithm
 for blind source separation is proposed. The proposed algorithm
 is based on the kurtosis optimization method and the
 J-method. The proposed algorithm is compared with the J-
 method in terms of the number of iterations required to
 reach a convergence threshold of 0.002. The results are shown
 in Table 1. It can be seen that the proposed algorithm
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Acknowledgements

This work was supported by the National Natural Science
 Foundation of China (Grant No. 2001001042).

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