4 Conclusion

This contribution describes selected mostly unknown properties of the Least Square Error for the approximation of acquired data. The LSE method is non-invariant to the multiplication of a row of the extended matrix $[\mathbf{A}|\mathbf{b}]$. Also, in the case of non-existent metric between parameters, like a distance and a normal vector, the LSE based approximation should not be used.

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