## Component-based Quadratic Similarity Identification for Multivariate Gaussian Sources

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In this work, we investigate the component-based quadratic similarity identification [1] for multivariate Gaussian sources. Consider a concatenation of N independent blocks of correlated zero-mean Gaussian random variables with blocklength M for  $D_{\rm ID}$ -similarity identification, where n = MN is the length of the source sequence, and  $D_{\rm ID}$  the similarity threshold. The blocks are decorrelated by the Karhunen-Loève (KL) transform. As we consider a Gaussian source, the KL transform outputs M independent Gaussian components with their corresponding variances. Then, each individual component is processed by a  $D_{\rm ID}^{(m)}$ -admissible system, where  $D_{\rm ID}^{(m)}$  is the similarity threshold for the *m*-th component. A database vector is labeled as maybe, if and only if all its transform components are determined as maybe.

The bit allocation for the components is achieved by a constrained minimization of the overall  $\Pr\{\text{maybe}\}$ . We use  $\Pr\{\text{maybe}\} \approx e^{-\frac{n}{M}\mathbb{E}_{\text{ID}}}$  for large  $\frac{n}{M}$ , where  $\mathbb{E}_{\text{ID}}$  is the *identification exponent* [1]. This leads to a maximization of the average identification exponent of M components subject to the total *identification rate* constraint  $R_{\text{ID}}$  and the similarity constraint  $D_{\text{ID}}$ . The latter guarantees that the M-component system maintains  $D_{\text{ID}}$ -admissibility.

$$\underbrace{\begin{array}{c} \underbrace{\tilde{y}_{m}}}_{\tilde{y}_{M}} \\ \underbrace{\tilde{y}_{M}}\\ \vdots\\ \underbrace{\tilde{y}_{M}} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{D_{\text{ID}}^{(m)} \text{-admissible System}} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{D_{\text{ID}}^{(m)} \text{-admissible System}} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{D_{\text{ID}}^{(m)} \text{-admissible System}} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{D_{\text{ID}}^{(m)} \text{-admissible System}} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{D_{\text{ID}}^{(m)} \text{-admissible System}} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{\tilde{y}_{M} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{\tilde{y}_{M} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{\tilde{y}_{M} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{\tilde{y}_{M} \\ \underbrace{\tilde{y}_{M}} \\ \underbrace{\tilde{y}$$

We consider the special case where one component forms a  $MD_{\rm ID}$ -admissible system. For the bit allocation problem, it can be shown that the sum of identification exponents is a quasiconcave function of the assigned component rates. Using quasiconcave programming [2], we show that the minimum *D*-achievable rate for this setting is achieved by the identification rate of the component with the largest variance.

- A. Ingber, T. Courtade, and T. Weissman, "Compression for quadratic similarity queries," *IEEE Trans. on Information Theory*, vol. 61, no. 5, pp. 2729 –2747, May 2015.
- [2] K. J. Arrow and A. Enthoven, "Quasi-concave programming," *Econometrica*, vol. 29, no. 4, pp. 779–800, 1961.