# AN ALGORITHM FOR CONSTRAINED ORTHOGONALIZATION 

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#### Abstract

This paper presents a procedure for the generation of an orthogonal set of functions, starting from a set of linearly independent non-orthogonal functions. The main characteristic of the algorithm is to produce the minimal perturbation on the original set.


Keywords: Orthonormal functions; Gram-Schmidt orthonormalization; Signal representation; Orthonormal bases.

## 1. INTRODUCTION

Bases for signal representation are perhaps the most important tool for signal processing and analysis [1], [2], [3], [5], [6], [7], [8], [9], [10]. The action of decomposing a signal through a base formed by a set of suitable signals is present in almost all procedures currently adopted to convey or to extract information. The orthogonal bases are massively employed mainly because they allow a simple decoupled computation of the coefficients of a signal representation.

The well known Gram-Schmidt procedure generates orthogonal functions starting from a set of linearly independent functions. However, the procedure leads to new functions whose shapes can be very different from the original ones.

A new procedure to orthogonalize a set of linearly independent functions is proposed in this paper. Its main characteristic is to preserve, subject to some criterion, the shapes of the original base components. A comparison with the classical Gram-Schmidt procedure is provided.

## 2. GRAM-SCHMIDT

Consider the set $\mathcal{N}$ of linearly independent real functions $f_{n}(t), n=1, \ldots, N$ with finite energy. A signal $y(t)$ not necessarily belonging to the space $\mathcal{S}_{N}$ spanned by the set $\mathcal{N}$ can be approximately expressed as

$$
\begin{equation*}
y(t) \cong \sum_{n=1}^{N} \alpha_{n} f_{n}(t) \tag{1}
\end{equation*}
$$

The coefficients $\alpha_{n}$ that minimize the mean square error

$$
\begin{equation*}
\left\langle\epsilon^{2}(t)\right\rangle=\int_{-\infty}^{+\infty}\left[y(t)-\sum_{n=1}^{N} \alpha_{n} f_{n}(t)\right]^{2} d t \tag{2}
\end{equation*}
$$

are given by

$$
\begin{equation*}
\alpha=R^{-1}\langle f y(t)\rangle \tag{3}
\end{equation*}
$$

where $\alpha \in \mathbb{R}^{N}$ and $f=\left[f_{1}(t) \ldots f_{N}(t)\right]^{\prime}$ are column vectors. The correlation matrix $\left\langle R=f f^{\prime}\right\rangle$ is composed by the elements

$$
\begin{equation*}
r_{k l}=\left\langle f_{k}(t) f_{l}(t)\right\rangle=\int_{-\infty}^{+\infty} f_{k}(t) f_{l}(t) d t \text { for } k, l=1, \ldots, N \tag{4}
\end{equation*}
$$

Note that the calculation of each coefficient $\alpha_{n}$ simultaneously involves all the $f_{n}(t)$ functions. If the set $\mathcal{N}$ is composed by orthogonal functions then $R$ is a diagonal matrix and each coefficient $\alpha_{n}$ can be calculated only from the corresponding $f_{n}(t)$ function and the signal $y(t)$.

To orthogonalize the set $\mathcal{N}$, consider the non-singular matrix $Q \in \mathbb{R}^{N \times N}$ which produces the linear transformation

$$
\begin{equation*}
g \triangleq Q f \tag{5}
\end{equation*}
$$

Note that the vector of functions $g$ produces a new base that spans the same space $\mathcal{S}_{N}$ that the one generated by $f$. The orthonormalization requires that $\left\langle g g^{\prime}\right\rangle=\mathbf{I}$ yielding

$$
\begin{equation*}
Q R Q^{\prime}=\mathbf{I} \tag{6}
\end{equation*}
$$

Equation (6) can be viewed as a system of quadratic equations with $N^{2}$ unknown variables and $N(N+1) / 2$ constraints, since by construction $R$ is a symmetric positive definite matrix [5]. As a consequence, there are several different ways to generate the orthonormal base $g$ from the given set of linearly independent functions $f$.

The symmetry and the positive definiteness characteristics of $R$ allow to obtain a solution of equation (6) by applying the Cholesky factorization to $R$, producing a lower triangular matrix $L$ such that $R=L L^{\prime}$ [4], yielding

$$
\begin{equation*}
Q R Q^{\prime}=(Q L)(Q L)^{\prime}=\mathbf{I} \tag{7}
\end{equation*}
$$

The Cholesky factorization induces $Q=L^{-1}$ as a solution of (6), which is the classical Gram-Schmidt orthonormalization.

To illustrate, consider the set of five linearly independent triangular functions $f_{n}(t)=f(t-n T)$ for $n=1, \ldots, 5$ where

$$
f(t)=\left\{\begin{array}{l}
(t / T)+1 \text { for }-T \leq t<0  \tag{8}\\
-(t / T)+1 \text { for } 0 \leq t \leq T \\
0 \quad \text { elsewhere }
\end{array}\right.
$$

with $T=1.5$ as illustrated in the figure 1 .


Figure 1: Triangular pulse that approximates the sampling function $\mathrm{Sa}(\pi t / T)$.

The correlation matrix $R$ (which is a tri-diagonal matrix) and the corresponding linear transformation $Q=L^{-1}$ for this example are given by

$$
\begin{gather*}
R=\left[\begin{array}{ccccc}
1 & 0.25 & 0 & 0 & 0 \\
0.25 & 1 & 0.25 & 0 & 0 \\
0 & 0.25 & 1 & 0.25 & 0 \\
0 & 0 & 0.25 & 1 & 0.25 \\
0 & 0 & 0 & 0.25 & 1
\end{array}\right] \\
Q=\left[\begin{array}{ccccc}
+1.000 & 0 & 0 & 0 & 0 \\
-0.258 & +1.033 & 0 & 0 & 0 \\
+0.069 & -0.276 & +1.035 & 0 & 0 \\
-0.019 & +0.074 & -0.277 & +1.035 & 0 \\
+0.005 & -0.019 & +0.074 & -0.277 & +1.035
\end{array}\right] \tag{10}
\end{gather*}
$$

Figure 2 shows the orthonormalized functions $g$. As it is well known, the classical Gram-Schmidt orthonormalization procedure is such that $g_{1}(t)=f_{1}(t)$ but $g_{n}(t) \neq f_{n}(t)$ for $n=2, \ldots, N$ and the changes on the original shapes are more important as $n$ increases.


Figure 2: Functions $g$ produced by the Gram-Schmidt orthonormalization procedure applied on the triangular functions $f$.

## 3. CONSTRAINED ORTHOGONALIZATION

The aim of the procedure proposed here is, of course, to orthogonalize the original set but obtaining a set of functions that best preserves the shapes of the original functions. For that, a quadratic criterion is used.

The problem becomes

$$
\begin{equation*}
\min _{g=Q f ; g \text { orthogonal }} \sum_{n=1}^{N} \int_{-\infty}^{+\infty}\left[g_{n}(t)-f_{n}(t)\right]^{2} d t \tag{11}
\end{equation*}
$$

Let the vectors $f_{\Delta}$ and $g_{\Delta}$ be the functions sampled with a period $\Delta$, yielding the approximative numerical computation for the correlation matrix $R$ :

$$
\begin{equation*}
R \cong f_{\Delta} f_{\Delta}^{\prime} \Delta \tag{12}
\end{equation*}
$$

Therefore, problem (11) can be written as

$$
\begin{align*}
& g_{\Delta}=Q f_{\Delta} ; \Delta g_{\Delta} g_{\Delta}^{\prime}=\mathbf{I} \operatorname{Tr}\left[\left(g_{\Delta}-f_{\Delta}\right)\left(g_{\Delta}-f_{\Delta}\right)^{\prime}\right] \Delta  \tag{13}\\
& \min _{Q R Q^{\prime}=\mathbf{I}} \operatorname{Tr}\left[Q R Q^{\prime}+R-Q R-R Q^{\prime}\right] \tag{14}
\end{align*}
$$

where $\operatorname{Tr}(\cdot)$ stands for trace of the square matrix argument, that is, $\operatorname{Tr}(M)=\sum_{i=1}^{n} m_{i i}$ for $M \in \mathbb{R}^{n \times n}$.

The solution to problem (14) also solves

$$
\begin{equation*}
\max _{Q R Q^{\prime}=\mathbf{I}} \operatorname{Tr}[2 R Q] \tag{15}
\end{equation*}
$$

which involves the maximization of a linear cost function subject to quadratic constraints. Since $R$ is a positive definite matrix, this problem has only one solution, which can be obtained using the Lagrange multiplier $Y$.

The Lagrangian function is given by

$$
\begin{equation*}
l(Q, Y)=\operatorname{Tr}\left[2 R Q+Y^{\prime}\left(Q R Q^{\prime}-\mathbf{I}\right)\right] \tag{16}
\end{equation*}
$$

yielding the stationary conditions [11]

$$
\begin{equation*}
Q R Q^{\prime}=\mathbf{I} \quad ; \quad 2 R+Y Q R+Y^{\prime} Q R=0 \tag{17}
\end{equation*}
$$

Note that the constraint $Q R Q^{\prime}=\mathbf{I}$ is symmetric implying that $Y^{\prime}=Y$ and $Y=-Q^{-1}$ which, applied to $Q R Q^{\prime}=\mathbf{I}$ leads to $Y^{2}=R$. Thus, the optimal solution of (15) is $Q=R^{-0.5}$.

As $R$ is a real symmetric positive definite matrix

$$
\begin{equation*}
Q=R^{-0.5}=U \Lambda^{-0.5} U^{\prime} \tag{18}
\end{equation*}
$$

where $U$ is a unitary matrix (i.e. $U^{\prime} U=\mathbf{I}$ ) and $\Lambda$ is a diagonal matrix formed by the eigenvalues of $R$ [4].

Observe that the solution $Q$ is a symmetric matrix. Indeed, by imposing this condition on equation (6) and applying the Schur decomposition on $R$ [4], one gets

$$
\begin{equation*}
R=U \Lambda U^{\prime} \Longrightarrow Q=U \Lambda^{-0.5} U^{\prime} \triangleq R^{-0.5} \tag{19}
\end{equation*}
$$

Figure 3 shows the proposed constrained orthonormalization applied to the triangular functions given in (8). Matrix $Q$ is given by

$$
Q=\left[\begin{array}{lllll}
+1.026 & -0.136 & +0.027 & -0.006 & +0.001  \tag{20}\\
-0.136 & +1.053 & -0.142 & +0.029 & -0.006 \\
+0.027 & -0.142 & +1.054 & -0.142 & +0.027 \\
-0.006 & +0.029 & -0.142 & +1.053 & -0.136 \\
+0.001 & -0.006 & +0.027 & -0.136 & +1.026
\end{array}\right]
$$

Note that the symmetry of matrix $Q$ results in a small perturbation equally distributed in all the original functions.

## 4. A TWO-DIMENSIONAL EXAMPLE

A better geometric understanding of the method proposed is illustrated through a simple example in a Cartesian plan.

Consider the matrix $F \in \mathbb{F}^{2 \times 2}$ composed by two linearly independent row vectors and the corresponding correlation matrix $R$ given by

$$
F=\left[\begin{array}{cc}
0 & 1  \tag{21}\\
0.707 & 0.707
\end{array}\right] \quad ; \quad R=\left[\begin{array}{cc}
1 & 0.707 \\
0.707 & 1
\end{array}\right]
$$



Figure 3: Functions $g$ produced by the constrained orthonormalization procedure applied on the triangular functions $f$.

The linear transformations that produce the Gram-Schmidt and the constrained orthonormalizations are given respectively by

$$
\left[\begin{array}{cc}
1 & 0  \tag{22}\\
-1 & 1.414
\end{array}\right] ; \quad\left[\begin{array}{cc}
1.307 & -0.541 \\
-0.541 & 1.307
\end{array}\right]
$$

and the two resulting orthonormal sets $g$ (i.e. unitary matrices) are respectively

$$
\left[\begin{array}{ll}
0 & 1  \tag{23}\\
1 & 0
\end{array}\right] ;\left[\begin{array}{cc}
-0.383 & 0.924 \\
0.924 & 0.383
\end{array}\right]
$$

Figure 4 shows that the resulting vectors in the constrained orthogonalization are equally perturbed with respect to the original vectors whereas in the Gram-Schmidt procedure the first vector is preserved and the second one is modified.


Figure 4: Resulting vectors for the two dimensional example.

## 5. CONCLUSION

A new procedure to orthogonalize a set of linearly independent functions has been presented. The algorithm is similar
to the classical Gram-Schmidt one, but presents the additional feature of minimizing the total mean square difference between the original functions and the corresponding orthogonal ones.

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