# CONSTRUCTION OF SLICED MAXIMIN-ORTHOGONAL LATIN HYPERCUBE DESIGNS 

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#### Abstract

A sliced Latin hypercube design is a special Latin hypercube design that can be divided into slices of smaller Latin hypercube designs. This type of designs is useful for computer experiments with qualitative and quantitative factors, multiple experiments, data pooling, and cross-validation. Orthogonality and uniformity are important properties for Latin hypercube designs. In this paper, sliced maximin-orthogonal Latin hypercube designs are constructed using orthogonal designs, Goethals-Seidel arrays, and Kharaghani arrays. The resulting designs have both second-order orthogonality and good uniformity.


Key words and phrases: Computer experiment, maximin distance, orthogonality, sliced Latin hypercube design.

## 1. Introduction

Sliced Latin hypercube designs (LHDs), first introduced by Qian (2012), are useful for computer experiments with qualitative and quantitative factors, multiple computer experimentations, data pooling, and cross-validation. Such a design is a special type of LHD, which can be divided into slices of smaller LHDs. Orthogonality and uniformity are two desirable properties for LHDs. An LHD is orthogonal if the inner product of any two columns is zero. It is second-order orthogonal if both the inner product of any two columns and the sum of the elementwise products of any three columns are zero, desirable when quadratic effects and bilinear interactions are present. Such a design guarantees that the estimates of all linear effects are uncorrelated with each other, and with that of all quadratic effects and bilinear interactions (cf., Ye (1998), Sun, Liu, and Lin (2010), Yang and Liu (20I2)). Construction of orthogonal and nearly orthogonal LHDs has been actively studied, including Ye (1998), Steinberg and Lin (2006), Cioppa and Lucas (2007), Georgiou (2009), Pang, Liu, and Lin (2009), Lin, Mukerjee, and Tang (2009), Bingham, Sitter, and Tang (2009), Sun, Liu, and Lin (2009, 2010), Lin et all (2010), Georgiou and Stylianou (201), Yang and Lin (2012), Ai, He, and Liu (2012), and Georgiou and Efthimiou (2014), among others. Apart from the orthogonality, experimenters are also interested in
spreading the points evenly across the experimental region. Johnson, Moore, and Ylvisaker (1990) introduced the maximin distance criterion, which maximizes the minimum inter-site distance. Morris and Mitchell (1995) applied this criterion for finding optimal LHDs.

The sliced LHDs proposed by Qian ( 2012 ) can only achieve a one-dimensional uniformity, but not orthogonality. Recently, Yang et al. (2013) and Huang, Yang, and Lin (2013) proposed methods to construct sliced LHDs with orthogonality or near orthogonality, but not good uniformity; Based on (resolvable) orthogonal arrays, Yin, Lin, and Liu (2014) and Yang, Chen, and Liu (2014) constructed sliced LHDs with an attractive low-dimensional uniformity, but not orthogonality. In this paper, we propose a new class of sliced LHDs, called sliced maximinorthogonal LHDs which are sliced orthogonal LHDs with good uniformity. Three construction methods for sliced orthogonal LHDs are presented. Then through an optimal column-exchange algorithm, sliced maximin-orthogonal LHDs from the resulting sliced orthogonal LHDs are obtained. The number of slices of the constructed designs is rather flexible.

The remainder of this paper is organized as follows. Section 2 presents the construction of sliced orthogonal LHDs. The sliced maximin-orthogonal LHDs are obtained in Section 3. Properties of the resulting designs are discussed in Section 4. All proofs are deferred to the Appendix.

## 2. Construction of Sliced Orthogonal LHDs

This section provides three methods for constructing sliced orthogonal LHDs with $k$ slices, where $k$ is a positive integer. We first introduce some relevant definitions and notations. An LHD with $n$ runs and $m$ factors, denoted by $L(n, m)$, has each column composed of $n$ equally-spaced levels. For convenience, the $n$ levels are taken to be $\{-(n-1),-(n-3), \ldots,(n-1)\}$. An $L(n, m)$ with $n=q k$ is called a sliced LHD, if it can be divided into $k$ slices each of which becomes an $L(q, m)$ when the $n$ levels are collapsed to $q$ equally-spaced levels according to:

$$
\begin{aligned}
& \{-(n-1),-(n-3), \ldots,-(n-2 k+1)\} \rightarrow-(q-1) \\
& \{-(n-2 k-1),-(n-2 k-3), \ldots,-(n-4 k+1)\} \rightarrow-(q-3), \ldots \\
& \{n-2 k+1, n-2 k+3, \ldots, n-1\} \rightarrow q-1
\end{aligned}
$$

Hence, the $q$ levels of each slice correspond to the $q$ equally-spaced intervals $[-n,-n+2 k),[-n+2 k,-n+4 k), \ldots,[n-4 k, n-2 k),[n-2 k, n)$. A sliced $L(n, m)$ with $n=q k$ is called orthogonal, denoted by $\operatorname{SOL}(n, m, k)$, if the whole design is orthogonal as well as design within each slice.

Suppose $S=\left\{S_{i}: S_{i}=\left(s_{i 0}, s_{i 1}, \ldots, s_{i(n-1)}\right), i=1, \ldots, k\right\}$ is a set of $k$ vectors of length $n$. The $t$ periodic autocorrelation function (PAF) of $S$ is defined as

$$
P_{S}(t)=\sum_{i=1}^{k} P_{S_{i}}(t)=\sum_{i=1}^{k} \sum_{j=0}^{n-1} s_{i j} s_{i, j+t}, \quad t=0, \ldots, n-1,
$$

where $j+t$ equals $(j+t) \bmod n$ when $j+t \geq n$. $S$ is said to have a zero PAF if $P_{S}(t)=0$, for any $t=1, \ldots, n-1$.

Suppose $v$ is a vector of order $m$, the circulant matrix with $v$ as the first row is a square matrix of order $m$, denoted by $C(v)$, where each row vector is rotated one element to the right relative to the preceding row vector.

### 2.1. Construction using orthogonal designs

In this subsection, sliced orthogonal LHDs are constructed via a special type of orthogonal design (OD) (see Yang and Liu (2012)).

Definition 1 (Yang and Liu (2012)). An $m \times m$ matrix $D$ is an $m$-order OD with entries from $\pm(i a+b)$ for $i=0, \ldots, m-1$ and $a \neq 0$, denoted by $O D(m)$, if it satisfies the properties: by changing $-(i a+b)$ to $i a+b$ (for $i=0, \ldots, m-1$ ) in $D$, each column is a permutation of $\{i a+b, i=0, \ldots, m-1\}$; the inner product of any two distinct columns is zero.
$O D(m)$ 's are available in Yang and Liu (2012) for $m=2^{r}$, where $r$ is any positive integer. A new construction method for sliced orthogonal LHDs with $k$ slices can be obtained by the following algorithm. It is able to construct an $S O L\left(k \cdot 2^{r+1}, 2^{r}, k\right)$ for any positive integer $r$, where the factor number is $2^{r}$. New sliced LHDs (with other numbers of factors) will be presented.

## Algorithm 1.

Step 1. Construct an $O D\left(2^{r}\right)$, denoted by $D_{a b}$, with elements of the form $\pm(j a+$ b) for $j=0, \ldots, 2^{r}-1$, where $a \neq 0$.

Step 2. Set $L_{i}=\left(D_{2 k, 2 i-1}^{T},-D_{2 k, 2 i-1}^{T}\right)^{T}$, for $i=1, \ldots, k$.
Step 3. The final design $L$ is obtained by stacking $L_{1}, \ldots, L_{k}$ row by row, $L=$ $\left(L_{1}^{T}, \ldots, L_{k}^{T}\right)^{T}$.

Theorem 1. An $L$ constructed by Algorithm 1 is an $\operatorname{SOL}(2 k m, m, k)$ with $k$ slices $L_{1}, \ldots, L_{k}$, where $m=2^{r}$ and $L_{i}$ is an orthogonal $L(2 m, m)$. When projected onto each dimension, each of the $2 m$ equally-spaced intervals $[-2 \mathrm{~km}$, $-2 k(m-1)),[-2 k(m-1),-2 k(m-2)), \ldots,[-2 k, 0),[0,2 k), \ldots,[2 k(m-1), 2 k m)$ contains exactly one point of each slice.

An example is given to illustrate the construction.

Example 1. Let $r=k=2$, then $m=2^{r}=4, n=2 k m=16$. Following Step 1, construct the $O D(4)$ with

$$
D_{a b}=\left(\begin{array}{rrrr}
b & a+b-3 a-b & 2 a+b \\
a+b & -b-2 a-b-3 a-b \\
2 a+b & 3 a+b & a+b & -b \\
3 a+b-2 a-b & b & a+b
\end{array}\right) .
$$

Take $a=4$, and for $b=1,3$, we have

$$
D_{41}=\left(\begin{array}{rrrr}
1 & 5 & -13 & 9 \\
5 & -1 & -9 & -13 \\
9 & 13 & 5 & -1 \\
13 & -9 & 1 & 5
\end{array}\right) \text { and } D_{43}=\left(\begin{array}{rrrr}
3 & 7 & -15 & 11 \\
7 & -3 & -11 & -15 \\
11 & 15 & 7 & -3 \\
15 & -11 & 3 & 7
\end{array}\right) .
$$

Let $L=\left(D_{41}^{T},-D_{41}^{T}, D_{43}^{T},-D_{43}^{T}\right)^{T}$, then $L$ is an $S O L(16,4,2)$ with 2 slices: $L_{1}=$ $\left(D_{41}^{T},-D_{41}^{T}\right)^{T}$ and $L_{2}=\left(D_{43}^{T},-D_{43}^{T}\right)^{T}$, where $L_{1}$ and $L_{2}$ are two orthogonal $L(8,4)$ 's, and

$$
\begin{aligned}
& L=\left(L_{1}^{T}, L_{2}^{T}\right)^{T} \\
& =\left(\begin{array}{rrrrrrrr|rrrrrrrr}
1 & 5 & 9 & 13 & -1 & -5 & -9 & -13 & 3 & 7 & 11 & 15 & -3 & -7 & -11 & -15 \\
5 & -1 & 13 & -9 & -5 & 1 & -13 & 9 & 7 & -3 & 15 & -11 & -7 & 3 & -15 & 11 \\
-13 & -9 & 5 & 1 & 13 & 9 & -5 & -1 & -15 & -11 & 7 & 3 & 15 & 11 & -7 & -3 \\
9 & -13 & -1 & 5 & -9 & 13 & 1 & -5 & 11 & -15 & -3 & 7 & -11 & 15 & 3 & -7
\end{array}\right)^{T} .
\end{aligned}
$$

### 2.2. Construction using Goethals-Seidel arrays

We next propose a method to construct sliced orthogonal LHDs by applying the Goethals-Seidel arrays. A Goethals-Seidel array is of the form

$$
G S\left(S_{1}, S_{2}, S_{3}, S_{4}\right)=\left(\begin{array}{cccc}
S_{1} & S_{2} R_{p} & S_{3} R_{p} & S_{4} R_{p} \\
-S_{2} R_{p} & S_{1} & -S_{4}^{T} R_{p} & S_{3}^{T} R_{p} \\
-S_{3} R_{p} & S_{4}^{T} R_{p} & S_{1} & -S_{2}^{T} R_{p} \\
-S_{4} R_{p} & -S_{3}^{T} R_{p} & S_{2}^{T} R_{p} & S_{1}
\end{array}\right)
$$

where $R_{p}$ is the back-diagonal identity matrix of order $p$, and $S_{1}, S_{2}, S_{3}$, and $S_{4}$ are circulant matrices of order $p$ (Goethals and Seidell ([967)).

Lemma 1 (Geramita and Seberry ([979), Thm. 4.49). If the circulant matrices $S_{1}, S_{2}, S_{3}$, and $S_{4}$ satisfy

$$
S_{1} S_{1}^{T}+S_{2} S_{2}^{T}+S_{3} S_{3}^{T}+S_{4} S_{4}^{T}=f I_{p}
$$

then $G S\left(S_{1}, S_{2}, S_{3}, S_{4}\right)$ is an orthogonal matrix of order $4 p$.

Corollary 1. If there exist vectors $S_{1}, S_{2}, S_{3}, S_{4}$ of length $p$ with zero PAF, then they can be used as the first rows of circulant matrices that can be placed in the Goethals-Seidel array to obtain an orthogonal matrix.

The key issue here is to obtain the sliced structure by constructing appropriate Goethals-Seidel arrays.

## Algorithm 2.

Step 1. Find vectors $v_{1}, v_{2}, v_{3}$, and $v_{4}$ of the same length $p$ with zero PAF, where the elements come from the set $\{b, b+a, \ldots, b+(4 p-1) a\}$ if the signs are ignored.
Step 2. Place the circulant matrices $C\left(v_{1}\right), C\left(v_{2}\right), C\left(v_{3}\right)$, and $C\left(v_{4}\right)$ into a Goethals-Seidel array to obtain $G_{a b}=G S\left(C\left(v_{1}\right), C\left(v_{2}\right), C\left(v_{3}\right), C\left(v_{4}\right)\right)$.
Step 3. For a given $k$, set $L_{i}=\left(G_{2 k, 2 i-1}^{T},-G_{2 k, 2 i-1}^{T}\right)^{T}$, for $i=1, \ldots, k$. Construct $L$ by stacking $L_{1}, \ldots, L_{k}$ row by row, $L=\left(L_{1}^{T}, \ldots, L_{k}^{T}\right)^{T}$.
Theorem 2. An L constructed by Algorithm 2 is an $\operatorname{SOL}(8 k p, 4 p, k)$ with $k$ slices $L_{1}, \ldots, L_{k}$, where $L_{i}$ is an orthogonal $L(8 p, 4 p)$. When projected onto each dimension, each of the $8 p$ equally-spaced intervals $[-8 p k,-(8 p k-2 k)), \ldots,[-2 k, 0)$, $[0,2 k), \ldots,[8 p k-2 k, 8 p k)$ contains exactly one point of each slice.

Example 2. With $k=p=3$, an $S O L(72,12,3)$ can be obtained where each slice is an $L(24,12)$. Take the vectors

$$
\begin{aligned}
& v_{1}=(7 a+b,-(2 a+b), 9 a+b), v_{2}=(8 a+b,-(10 a+b), 11 a+b), \\
& v_{3}=(b, a+b,-(3 a+b)), \text { and } \quad v_{4}=(4 a+b, 5 a+b, 6 a+b),
\end{aligned}
$$

where $a$ and $b$ can be any real numbers. It is easy to calculate that

$$
\begin{aligned}
P_{v_{1}}(0)+P_{v_{2}}(0)+P_{v_{3}}(0)+P_{v_{4}}(0) & =12 b^{2}+132 a b+506 a^{2}, \text { and } \\
P_{v_{1}}(t)+P_{v_{2}}(t)+P_{v_{3}}(t)+P_{v_{4}}(t) & =0, \text { for } t=1,2 .
\end{aligned}
$$

Then $G_{61}, G_{63}, G_{65}$ can be obtained separately, as

$$
G_{61}=\left(\begin{array}{rrr|rrr|rrr|rrr}
43 & -13 & 55 & 67 & -61 & 49 & -19 & 7 & 1 & 37 & 31 & 25 \\
55 & 43 & -13 & -61 & 49 & 67 & 7 & 1 & -19 & 31 & 25 & 37 \\
-13 & 55 & 43 & 49 & 67 & -61 & 1 & -19 & 7 & 25 & 37 & 31 \\
\hline-67 & 61 & -49 & 43 & -13 & 55 & -31 & -37 & -25 & 7 & -19 & 1 \\
61 & -49 & -67 & 55 & 43 & -13 & -37 & -25 & -31 & -19 & 1 & 7 \\
-49 & -67 & 61 & -13 & 55 & 43 & -25 & -31 & -37 & 1 & 7 & -19 \\
\hline 19 & -7 & -1 & 31 & 37 & 25 & 43 & -13 & 55 & 61 & -67 & -49 \\
-7 & -1 & 19 & 37 & 25 & 31 & 55 & 43 & -13 & -67 & -49 & 61 \\
-1 & 19 & -7 & 25 & 31 & 37 & -13 & 55 & 43 & -49 & 61 & -67 \\
\hline-37 & -31 & -25 & -7 & 19 & -1 & -61 & 67 & 49 & 43 & -13 & 55 \\
-31 & -25 & -37 & 19 & -1 & -7 & 67 & 49 & -61 & 55 & 43 & -13 \\
-25 & -37 & -31 & -1 & -7 & 19 & 49 & -61 & 67 & -13 & 55 & 43
\end{array}\right),
$$

$$
\begin{aligned}
& G_{63}=\left(\begin{array}{rrr|rrr|rrr|rrr}
45 & -15 & 57 & 69 & -63 & 51 & -21 & 9 & 3 & 39 & 33 & 27 \\
57 & 45 & -15 & -63 & 51 & 69 & 9 & 3 & -21 & 33 & 27 & 39 \\
-15 & 57 & 45 & 51 & 69 & -63 & 3 & -21 & 9 & 27 & 39 & 33 \\
\hline-69 & 63 & -51 & 45 & -15 & 57 & -33 & -39 & -27 & 9 & -21 & 3 \\
63 & -51 & -69 & 57 & 45 & -15 & -39 & -27 & -33 & -21 & 3 & 9 \\
-51 & -69 & 63 & -15 & 57 & 45 & -27 & -33 & -39 & 3 & 9 & -21 \\
\hline 21 & -9 & -3 & 33 & 39 & 27 & 45 & -15 & 57 & 63 & -69 & -51 \\
-9 & -3 & 21 & 39 & 27 & 33 & 57 & 45 & -15 & -69 & -51 & 63 \\
-3 & 21 & -9 & 27 & 33 & 39 & -15 & 57 & 45 & -51 & 63 & -69 \\
\hline-39 & -33 & -27 & -9 & 21 & -3 & -63 & 69 & 51 & 45 & -15 & 57 \\
-33 & -27 & -39 & 21 & -3 & -9 & 69 & 51 & -63 & 57 & 45 & -15 \\
-27 & -39 & -33 & -3 & -9 & 21 & 51 & -63 & 69 & -15 & 57 & 45
\end{array}\right), \\
& G_{65}=\left(\begin{array}{rrrrrrrrrrr}
47 & -17 & 59 & 71 & -65 & 53 & -23 & 11 & 5 & 41 & 35 \\
59 & 47 & -17 & -65 & 53 & 71 & 11 & 5 & -23 & 35 & 29 \\
41 \\
-17 & 59 & 47 & 53 & 71 & -65 & 5 & -23 & 11 & 29 & 41 \\
\hline-71 & 65 & -53 & 47 & -17 & 59 & -35 & -41 & -29 & 11 & -23 \\
65 & -53 & -71 & 59 & 47 & -17 & -41 & -29 & -35 & -23 & 5 \\
\hline & 11 \\
-53 & -71 & 65 & -17 & 59 & 47 & -29 & -35 & -41 & 5 & 11 \\
\hline 23 & -11 & -5 & 35 & 41 & 29 & 47 & -17 & 59 & 65 & -71 \\
-11 & -5 & 23 & 41 & 29 & 35 & 59 & 47 & -17 & -71 & -53 \\
-5 & 23 & -11 & 29 & 35 & 41 & -17 & 59 & 47 & -53 & 65 \\
\hline-71 \\
\hline-41 & -35 & -29 & -11 & 23 & -5 & -65 & 71 & 53 & 47 & -17 \\
-35 & -29 & -41 & 23 & -5 & -11 & 71 & 53 & -65 & 59 & 47 \\
-29 & -41 & -35 & -5 & -11 & 23 & 53 & -65 & 71 & -17 & 59 \\
\hline
\end{array}\right) .
\end{aligned}
$$

If $L_{1}=\left(G_{61}^{T},-G_{61}^{T}\right)^{T}, L_{2}=\left(G_{63}^{T},-G_{63}^{T}\right)^{T}$, and $L_{3}=\left(G_{65}^{T},-G_{65}^{T}\right)^{T}$, then $L=$ $\left(L_{1}^{T}, L_{2}^{T}, L_{3}^{T}\right)^{T}$ is an $\operatorname{SOL}(72,12,3)$, where each $L_{i}$ is an orthogonal $L(24,12)$.

Example 3. With $k=2, p=5$, an $\operatorname{SOL}(80,20,2)$ can be obtained where each slice is an $L(40,20)$. Take the vectors

$$
\begin{aligned}
& v_{1}=(10 a+b, 2 a+b,-(13 a+b), 14 a+b, 11 a+b), \\
& v_{2}=(12 a+b, 15 a+b, 16 a+b, 17 a+b,-(18 a+b)), \\
& v_{3}=(19 a+b, b,-(a+b),-(3 a+b),-(4 a+b)), \text { and } \\
& v_{4}=(5 a+b, 6 a+b,-(7 a+b), 8 a+b,-(9 a+b)),
\end{aligned}
$$

where $a$ and $b$ can be any real numbers. It is easy to verify that

$$
\begin{aligned}
P_{v_{1}}(0)+P_{v_{2}}(0)+P_{v_{3}}(0)+P_{v_{4}}(0) & =20 b^{2}+380 a b+2470 a^{2}, \text { and } \\
P_{v_{1}}(t)+P_{v_{2}}(t)+P_{v_{3}}(t)+P_{v_{4}}(t) & =0, \text { for } t=1, \ldots, 4 .
\end{aligned}
$$

Then we can obtain $G_{41}$ and $G_{43}$ separately; they are presented in Appendix B. If $L_{1}=\left(G_{41}^{T},-G_{41}^{T}\right)^{T}$, and $L_{2}=\left(G_{43}^{T},-G_{43}^{T}\right)^{T}$, then $L=\left(L_{1}^{T}, L_{2}^{T}\right)^{T}$ is an $\operatorname{SOL}(80,20,2)$, where each $L_{i}$ is an orthogonal $L(40,20)$.

### 2.3. Construction using Kharaghani arrays

The third construction method is based on an important result due to Kharaghanil (2000).

Lemma 2 (Kharaghanil (2000), Thm. 1). Let $\left\{S_{1}, \ldots, S_{8}\right\}$ be a set of circulant matrices of order $p$, satisfying

$$
\sum_{i=1}^{8} S_{i} S_{i}^{T}=s I_{p} \text { and } \sum_{i=1}^{4}\left(S_{2 i-1} S_{2 i}^{T}-S_{2 i} S_{2 i-1}^{T}\right)=0
$$

Then the Kharaghani array

$$
\begin{aligned}
& K\left(S_{1}, \ldots, S_{8}\right) \\
& \quad=\left(\begin{array}{cccccccc}
S_{1} & S_{2} & S_{4} R_{p} & S_{3}^{T} R_{p} & S_{6} R_{p} & S_{5} R_{p} & S_{8} R_{p} & S_{7} R_{p} \\
-S_{2} & S_{1} & S_{3} R_{p} & -S_{4}^{T} R_{p} & S_{5} R_{p} & -S_{6} R_{p} & S_{7} R_{p} & -S_{8} R_{p} \\
-S_{4} R_{p}-S_{3} R_{p} & S_{1} & S_{2} & -S_{8}^{T} R_{p} & S_{7}^{T} R_{p} & S_{6}^{T} R_{p} & -S_{5}^{T} R_{p} \\
-S_{3} R_{p} & S_{4} R_{p} & -S_{2} & S_{1} & S_{7}^{T} R_{p} & S_{8}^{T} R_{p} & -S_{5}^{T} R_{p}-S_{6}^{T} R_{p} \\
-S_{6} R_{p}-S_{5} R_{p} & S_{8}^{T} R_{p} & -S_{7}^{T} R_{p} & S_{1} & S_{2} & -S_{4}^{T} R_{p} & S_{3}^{T} R_{p} \\
-S_{5} R_{p} & S_{6} R_{p} & -S_{7}^{T} R_{p}-S_{8}^{T} R_{p} & -S_{2} & S_{1} & S_{3}^{T} R_{p} & S_{4}^{T} R_{p} \\
-S_{8} R_{p}-S_{7} R_{p}-S_{6}^{T} R_{p} & S_{5}^{T} R_{p} & S_{4}^{T} R_{p} & -S_{3}^{T} R_{p} & S_{1} & S_{2} \\
-S_{7} R_{p} & S_{8} R_{p} & S_{5}^{T} R_{p} & S_{6}^{T} R_{p} & -S_{3}^{T} R_{p}-S_{4}^{T} R_{p} & -S_{2} & S_{1}
\end{array}\right)
\end{aligned}
$$

is an orthogonal matrix of order $8 p$.
Remark 1. As in Corollary 1, if there exist eight vectors of length $p$ with zero PAF, they can be used to generate eight suitable circulant matrices for Lemma 2.

The key issue here is to obtain the sliced structure by constructing appropriate Kharaghani arrays.

## Algorithm 3.

Step 1. Find eight vectors $v_{1}, \ldots, v_{8}$ of the same length $p$ with zero PAF satisfying

$$
\sum_{i=1}^{4}\left(C\left(v_{2 i-1}\right) C\left(v_{2 i}\right)^{T}-C\left(v_{2 i}\right) C\left(v_{2 i-1}\right)^{T}\right)=0
$$

where the elements come from the set $\{b, b+a, \ldots, b+(8 p-1) a\}$ if the signs are ignored.
Step 2. Place the eight circulant matrices $C\left(v_{1}\right), \ldots, C\left(v_{8}\right)$ into a Kharaghani array to obtain $K_{a b}=K\left(C\left(v_{1}\right), \ldots, C\left(v_{8}\right)\right)$.
Step 3. For a given $k$, set $L_{i}=\left(K_{2 k, 2 i-1}^{T},-K_{2 k, 2 i-1}^{T}\right)^{T}$, for $i=1, \ldots, k$. Obtain $L$ by stacking $L_{1}, \ldots, L_{k}$ row by row, $L=\left(L_{1}^{T}, \ldots, L_{k}^{T}\right)^{T}$.

Theorem 3. An L constructed by Algorithm 3 is an $\operatorname{SOL}(16 p k, 8 p, k)$ with $k$ slices $L_{1}, \ldots, L_{k}$, where $L_{i}$ is an orthogonal $L(16 p, 8 p)$. When projected onto each dimension, each of the $16 p$ equally-spaced intervals $[-16 p k,-(16 p k-2 k)), \ldots$, $[-2 k, 0),[0,2 k), \ldots,[16 p k-2 k, 16 p k)$ contains exactly one point of each slice.
Example 4. With $k=p=3$, an $S O L(96,24,2)$ can be obtained where each slice is an $L(48,24)$. Take the vectors

$$
\begin{array}{ll}
v_{1}=(b, 13 a+b, a+b), & v_{2}=(11 a+b,-(12 a+b), 14 a+b), \\
\left.v_{3}=(2 a+b, 3 a+b,-4 a+b)\right), & v_{4}=(15 a+b, 16 a+b,-(17 a+b)), \\
v_{5}=(5 a+b,-(6 a+b),-(7 a+b)), & v_{6}=(18 a+b, 19 a+b, 20 a+b), \\
v_{7}=(8 a+b, 9 a+b,-(10 a+b)), \text { and } v_{8}=(21 a+b, 22 a+b,-(23 a+b)) .
\end{array}
$$

It is easy to verify that

$$
\begin{aligned}
& \sum_{i=0}^{8} P_{A_{i}}(0)=24 b^{2}+552 a b+4324 a^{2}, \quad \sum_{i=0}^{8} P_{A_{i}}(t)=0 \text { for } t=1, \ldots, 8, \text { and } \\
& \sum_{i=1}^{8} C\left(v_{i}\right) C\left(v_{i}\right)^{T}=c I_{p}, \text { with } c=24 b^{2}+552 a b+4324 a^{2} .
\end{aligned}
$$

Then we have $K_{41}$ and $K_{43}$; they can be found in Appendix B. If $L_{1}=\left(K_{41}^{T},-K_{41}^{T}\right)^{T}$ and $L_{2}=\left(K_{43}^{T},-K_{43}^{T}\right)^{T}$, then $L=\left(L_{1}^{T}, L_{2}^{T}\right)^{T}$ is an $\operatorname{SOL}(96,24,2)$, where each slice is an orthogonal $L(48,24)$.

## 3. Sliced Maximin-Orthogonal LHDs

In this section, the uniformity of LHDs measured by the maximin distance criterion is considered. Let $x_{u}=\left(x_{u}^{1}, \ldots, x_{u}^{m}\right)$ and $x_{v}=\left(x_{v}^{1}, \ldots, x_{v}^{m}\right)$ be two points in the experimental region $[-1,1]^{m}$, the distance between them is defined as

$$
d\left(x_{u}, x_{v}\right)=\left\{\sum_{j=1}^{m}\left|x_{u}^{j}-x_{v}^{j}\right|^{s}\right\}^{1 / s},
$$

where different values of $s$ correspond to different distances. Here, we take $s=2$, Euclidean distance. Given a design $D$, the minimum inter-site distance of $D$ is denoted by $d_{\text {min }}(D)$, where

$$
d_{\min }(D)=\min _{x_{u}, x_{v} \in D, u \neq v} d\left(x_{u}, x_{v}\right) .
$$

Due to Johnson, Moore, and Ylvisaker (1990), a maximin distance design $D_{*}$ maximizes the minimum inter-site distance $d_{\min }(D)$,

$$
d_{\min }\left(D_{*}\right)=\max _{D \in \mathcal{D}} d_{\min }(D)
$$

where $\mathcal{D}$ is the set of possible designs. In this section, sliced maximin-orthogonal LHDs are searched by a column-exchange algorithm from the designs constructed in Section 2, where threshold accepting (see Dueck and Scheuer ([19.90)) is used as the accept rule.

## Algorithm 4.

Step 1. Construct an initial $\operatorname{SOL}(n, m, k)$, denoted by $D_{0}$, then scale the levels $\{-(n-1),-(n-3), \ldots,(n-1)\}$ to $\{-(n-1) / n,-(n-3) / n, \ldots,(n-$ 1)/ $n\}$, and compute $d_{\min }\left(D_{0}\right)$, denoted by $d_{0}$. Set a sequence of threshold parameter $T h=\left(T_{1}, \ldots, T_{L}\right)$, where $T_{1}>\cdots>T_{L}>0$. Denote the iteration number by $I$ under each $T_{l}$ for $l=1, \ldots, L$. Set indices $l=$ $1, i=1$.

Step 2. Hold the first slice of $D_{0}$ unchanged, randomly choose a slice from the remaining ones, and choose two columns in that slice; exchange these two columns in the slice and get a new sliced LHD, denoted by $D_{\text {try }}$. Compute $d_{\text {min }}\left(D_{\text {try }}\right)$, denoted by $d_{\text {try }}$.
Step 3. If $d_{0}-d_{\text {try }} \leq T_{l}$, replace $D_{0}$ by $D_{\text {try }}$ and set $d_{0}=d_{\text {try }}$; else leave $D_{0}$ unchanged.
Step 4. Update $i=i+1$, if $i \leq I$, go to Step 2.
Step 5. Update $l=l+1$, if $l \leq L$, reset $i=1$ and go to Step 2; else deliver $D_{\text {best }}=D_{0}$.

Remark 2. An optimal design can thus be obtained by exchanging the columns of some slices. It is obvious that each slice of the optimal sliced LHD is still orthogonal after the exchange. Thus the optimal sliced LHD remains orthogonal.

Example 5 (Example 1 continued). Take the design $L$ constructed in Example 1 as the initial design $D_{0}, D_{0}=L=\left(L_{1}^{T}, L_{2}^{T}\right)^{T}=\left(D_{1}^{T},-D_{1}^{T}, D_{3}^{T},-D_{3}^{T}\right)^{T}$, and scale the levels $\{-15,-13, \ldots, 15\}$ to $\{-15 / 16,-13 / 16, \ldots, 15 / 16\}$.

Compute $d_{\min }\left(D_{0}\right)$, and get $d_{0}=d_{\min }\left(D_{0}\right)=0.25$. Following Algorithm 4, we obtain the sliced maximin-orthogonal LHD $D_{\text {best }}$ with $d_{\text {best }}=d_{\text {min }}\left(D_{\text {best }}\right)=$ 0.9682 , which greatly improves the initial design $D_{0}$, where
$D_{\text {best }}$
$=\left(\begin{array}{rrrrrrrr|rrrrrrrr}1 & 5 & 9 & 13 & -1 & -5 & -9 & -13 & 3 & 7 & 11 & 15 & -3 & -7 & -11 & -15 \\ 5 & -1 & 13 & -9 & -5 & 1 & -13 & 9 & -15 & -11 & 7 & 3 & 15 & 11 & -7 & -3 \\ -13 & -9 & 5 & 1 & 13 & 9 & -5 & -1 & 11 & -15 & -3 & 7 & -11 & 15 & 3 & -7 \\ 9 & -13 & -1 & 5 & -9 & 13 & 1 & -5 & 7 & -3 & 15 & -11 & -7 & 3 & -15 & 11\end{array}\right)^{T}$.
In fact, the transformation from $D_{0}$ to $D_{\text {best }}$ is that keeping the first slice $L_{1}$ of $D_{0}$ unchanged, and exchanging the four columns $1,2,3,4$ to $1,3,4,2$ in the second slice $L_{2}$. The improvement on $d_{\text {min }}$ can also be viewed intuitively by the bivariate projections of $D_{0}$ and $D_{\text {best }}$ in Figure 1, where X1, X2, X3 and X4 denote the four columns $1,2,3,4$ of $D_{0}$ and $D_{\text {best }}$, respectively.


Figure 1. Bivariate projections among the four columns of $D_{0}$ and $D_{\text {best }}$.
Table 1. The $d_{\text {min }}$ 's of the initial sliced orthogonal LHDs and maximinorthogonal ones.

| $S O L(n, m, k)$ | $(16,4,2)$ | $(32,8,2)$ | $(48,12,2)$ | $(72,16,2)$ | $(80,20,2)$ | $(96,24,2)$ | $(128,32,2)$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $d_{0}$ | 0.25 | 0.1768 | 0.1443 | 0.1250 | 0.2236 | 0.2041 | 0.0884 |
| $d_{\text {best }}$ | 0.9682 | 1.5989 | 2.0613 | 2.4343 | 5.3193 | 5.9307 | 3.5029 |

Note: $d_{0}$ denotes the $d_{\text {min }}$ of the initial design; $d_{\text {best }}$ means the $d_{\text {min }}$ of the optimal maximinorthogonal one found by Algorithm 4.

Table 1 tabulates the $d_{\text {min }}$ 's of some optimal sliced maximin-orthogonal LHDs best found by Algorithm 4 and the corresponding initial designs, where the initial designs with 12 and 20 columns can be constructed by Algorithm 2, the one with 24 columns can be obtained by Algorithm 3, and those with 4, 8, 16, and 32 columns can be easily obtained following Algorithm 1 and the construction of $O D\left(2^{r}\right)$ in Yang and Liu (2012). From Table 1, we can see that any of the sliced maximin-orthogonal LHDs gives a great improvement on the $d_{\text {min }}$ compared with the corresponding initial one.

## 4. Further Results and Discussion

The newly constructed sliced maximin-orthogonal LHDs not only have the orthogonality but also a good uniformity (measured by the maximin distance). These are desirable properties for LHDs. The numbers of slices of the constructed orthogonal designs are rather flexible, not obtainable by all existing methods. Given an integer $k$, sliced LHDs with $k$ slices can be constructed by Algorithms 1, 2, and 3. Each slice is an $L\left(2^{r+1}, 2^{r}\right)$ by Algorithm 1 ; an $L(8 p, 4 p)$ by Algorithm 2; and an $L(16 p, 8 p)$ by Algorithm 3. Then by Algorithm 4, the corresponding sliced

Table 2. The vectors for Goethals-Seidel arrays and Kharaghani arrays.

| $p$ | Order of array | Vectors |
| :---: | :---: | :---: |
| 3 | 12 | $\begin{array}{ll} v_{1}=(7 a+b,-(2 a+b), 9 a+b), v_{2}=(8 a+b,-(10 a+b), 11 a+b), \\ v_{3}=(b, a+b,-(3 a+b)), & v_{4}=(4 a+b, 5 a+b, 6 a+b) . \end{array}$ |
| 3 | 24 | $\begin{array}{ll} v_{1}=(b, 13 a+b, a+b), & v_{2}=(11 a+b,-(12 a+b), 14 a+b), \\ \left.v_{3}=(2 a+b, 3 a+b,-4 a+b)\right), & v_{4}=(15 a+b, 16 a+b,-(17 a+b)), \\ v_{5}=(5 a+b,-(6 a+b),-(7 a+b)), & v_{6}=(18 a+b, 19 a+b, 20 a+b), \\ v_{7}=(8 a+b, 9 a+b,-(10 a+b)), & v_{8}=(21 a+b, 22 a+b,-(23 a+b)) . \end{array}$ |
| 5 | 20 | $\begin{aligned} & v_{1}=(10 a+b, 2 a+b,-(13 a+b), 14 a+b, 11 a+b), \\ & v_{2}=(12 a+b, 15 a+b, 16 a+b, 17 a+b,-(18 a+b)), \\ & v_{3}=(19 a+b, b,-(a+b),-(3 a+b),-(4 a+b)), \\ & v_{4}=(5 a+b, 6 a+b,-(7 a+b), 8 a+b,-(9 a+b)) . \end{aligned}$ |

maximin-orthogonal LHDs can be obtained that are not available through other existing constructions. Combining fold-over structures and the sliced orthogonal LHDs constructed above, we have the following.

Theorem 4. For any of the sliced orthogonal or maximin-orthogonal LHDs constructed by Algorithms 1, ..., 4, the full design and each slice have second-order orthogonality.

Second-order orthogonality of a design is quite useful for effects screening and model fitting. In Step 1 of Algorithms 2 and 3, vectors with zero PAF should be found, and the algorithm in Section 3.1 of Georgiou and Efthimiou (2014) can be extended to search for such vectors. Details are omitted here. Table 2 lists the vectors for small $p$-they have been used in Examples 2, 3, and 4. With these vectors, sliced maximin-orthogonal LHDs with $k$ slices can then be constructed for any $k \geq 2$.

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## Appendix A: Proofs of Theorems

## A.1. Proof of Theorem 1.

For $m=2^{r}$, from the definitions of the OD and $L_{i}$, it is easy to verify that the levels of each column of $L_{i}$ are

$$
\{ \pm(2 i-1), \pm(2 k+2 i-1), \ldots, \pm(2 k(m-1)+2 i-1)\}, i=1, \ldots, k
$$

Since $L$ is obtained by stacking $L_{1}, \ldots, L_{k}$ row by row, the levels of each column of $L$ are

$$
\{ \pm 1, \pm 3, \ldots, \pm(2 k m-1)\}
$$

Furthermore, the $2 m$ levels of each $L_{i}$ are in the equally-spaced intervals

$$
\begin{array}{r}
{[-2 k m,-2 k(m-1)),[-2 k(m-1),-2 k(m-2)), \ldots,[-2 k, 0),[0,2 k), \ldots,} \\
{[2 k(m-1), 2 k m) .}
\end{array}
$$

This guarantees the sliced structure of $L$. The orthogonality of $L$ and $L_{i}$ follows from the orthogonality of the ODs.

## A.2. Proof of Theorem 2.

We first show that $L$ is a sliced LHD. From the structure of the GoethalsSeidel array $G_{a b}$, it is easy to see that each column of $G_{a b}$ is a permutation of $\{b, b+a, \ldots, b+(4 p-1) a\}$ without considering the signs. For a given $k$, from the definition of $L_{i}, i=1, \ldots, k$, it is easy to verify that the levels of each column of $L_{i}$ are $\{ \pm(2 i-1), \pm(2 k+2 i-1), \ldots, \pm(8 p k-2 k+2 i-1)\}$, which correspond to the $8 p$ equally-spaced intervals $[-8 p k,-(8 p k-2 k)), \ldots,[-2 k, 0),[0,2 k), \ldots,[8 p k-$ $2 k, 8 p k)$. This shows that $L_{i}$ is an $L(8 p, 4 p)$. Furthermore, the elements in each column of $L$ are $\{ \pm 1, \pm 3, \ldots, \pm(8 p k-1)\}$. This verifies that $L$ is a sliced LHD with $k$ sliced $L_{1}, \ldots, L_{k}$.

The orthogonality of $L$ and $L_{i}$ follows from the orthogonality of $G_{a b}$ which comes from Corollary 1.

## A.3. Proof of Theorem 3.

The proof of Theorem 3 is similar to that of Theorem 2.

## Appendix B: Design Matrices for Examples 3 and 4


$K_{41}=$



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