# RESPONSE MATRIX DECOMPOSITION ON SINGLE CONNECTION EDGES 

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#### Abstract

This paper gives a method of computing new response matrix from the old one when adding a boudary spike, and it proves a response matrix can be decomposed into a weighted average of two response matrices in some specific cases called single connections. In its conclusion, it also gives a realization of how a single connection affects the response matrix in a sense of geometry.


## 1. Introduction

The inverse problem of electrical networks has beed studied for more than ten years. According to the pass research, the recoverability on a circular planar network can be clearly realized thought out a corresponding medial graph. However, we have very little knowledge on non-circular-planar cases. This paper provides a simple view on the relationship between a conductance in a network and its response matrix in the easiest case - single connections. In order to state the idea explictly, we shall define the terminologies as the following:

Definition 1.1. A graph with boundary is a graph $G\left(V, V_{B}, E\right)$ with a set of vertices $V$ (also called nodes in the sense of electrical network), a set of edges $E$, where some of the vertices are set as boundary nodes $V_{B}$, see [1] p11. A vertex is called an interior node if it is not a boundary node. For convienence, a graph always denotes a graph with boundary in this paper. Addtionally, let a network denotes a graph with a conductance value assigned on each edge, and conductivity refers to an assignment of conductance values on all the edges in a graph in this paper.
Definition 1.2. A subgraph with boudary is a subgraph $G^{\prime}\left(V^{\prime}, V_{B}{ }^{\prime}, E^{\prime}\right)$ of $G\left(V, V_{B}, E\right)$ such that any node $v$ in $V^{\prime}$ is set to $V_{B}{ }^{\prime}$ if and only if $v \in V_{B}$ or not all of its adjacent edges are in $E^{\prime}$. It's easy to see the compliment of a subgraph with boundary is also a subgraph with boundary. Similarly, we simply use subgraph to denote subgraph with boundary thoughout this paper. For more interesting results about subgraph, see Jeff Russell's work [2]. The word subnetwork follows the same analogy.

Definition 1.3. A boundary spike is an edge connecting a boundary node and an interior node, such that it is the only edge adjacent to that boundary node. A boundary edge is an edge connecting two boundary nodes [1] p55-57.

Definition 1.4. A single connection edge is an edge in a connected graph such that removing it breaks the connectedness. A boundary spike is always a single connection edge. Any boundary edge doesn't count for a single connection.

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Remark 1.5. For response matrix, medial graph, circular-planarity, see [1]. Let $\Lambda(\Gamma)$ donotes the response matrix of a network $\Gamma$ thourghout this paper.
Remark 1.6. In this paper, a graph doesn't need to be circular-planar, and we shall consider all-positive conductivities. However, the concept in this paper also works for mix-signed cases with some minor problems (i.e. sigularities). For signed conductivities, see also [3].

## 2. Boundary Spike Computation

In this section, we work out how the response matrix changes when adding a boundary spike onto the network. Precisly, we shall pharse our statement as the following:

Lemma 2.1. Suppose $G\left(V, V_{B}, E\right)$ is a network with $V_{B}=\left\{V_{1}, V_{2}, \ldots, V_{n}\right\}$, and $V_{1}$ has a boundary spike $S$ connecting to an interior node $V_{0}$. Let $G^{\prime}\left(V^{\prime}, V_{B}{ }^{\prime}, E^{\prime}\right)$ be a subgraph of $G$, with $V^{\prime}=V-\left\{V_{1}\right\}, E^{\prime}=E-\{S\}$, and $V_{B}^{\prime}=\left\{V_{0}, V_{2}, \ldots, V_{n}\right\}$, then we have:

$$
\Lambda=\Lambda^{\prime}\left(\begin{array}{ccccc}
\frac{c}{c+\Lambda_{11}^{\prime}} & -\frac{\Lambda_{12}^{\prime}}{c+\Lambda_{11}^{\prime}} & -\frac{\Lambda_{13}^{\prime}}{c+\Lambda_{11}^{\prime}} & \cdots & -\frac{\Lambda_{1 n}^{\prime}}{c+\Lambda_{11}^{\prime}}  \tag{1}\\
& 1 & 1 & & \\
& & & \ddots & \\
& & & & 1
\end{array}\right)
$$

where $c$ is the conductance on $S, \Lambda_{i j}^{\prime}$ denotes the $i_{t h}$ row, $j_{t h}$ column entry of $\Lambda^{\prime}$ (also throughout this paper).

Proof. Use Schur complements, see [1] p57.

## 3. Contraction and Deletion

Definition 3.1. Suppose there is an edge $E$ connecting two vertices $A_{1}$ and $A_{2}$ in graph $G$. The contraction of $E$ removes $E$ and merges $A_{1}$ and $A_{2}$ into a vertex $A^{\prime}$ so that $A^{\prime}$ owns all the degrees of $A_{1}$ and $A_{2}$ originally. The deletion just removes $E$, and keeps $A_{1}$ and $A_{2}$ seperated. See [1] p16-17.

When we consider a conductance in an inclusive sense, the possible greatest value is positive infinite and the possible least value is zero. A positive infinite conductance on a network is equivalent to the corresponing edge contracted in the graph. Similarly, a zero conductance is equivalent to the edge deleted. Contraction and deletion therefore represent the two extreme conditions of the graph when a conductance varies from zero to positive infinite.

Given a conductance $c$ in a network $\Gamma$, let the networks after contraction and deletion of $c$ called $\Gamma^{C}$ and $\Gamma^{D}$ respectively, throughout this paper. If we consider the response matrix $\Lambda(\Gamma)$ as a point in the "response matrix space" (i.e. think each non-trivial entry in the matrix as a dimention in a geometric space.) when $c$ varies from zero to positive infinite, the trace should be a curve connecting from $\Lambda\left(\Gamma^{D}\right)$ to $\Lambda\left(\Gamma^{C}\right)$. Conceptionally, we shall think of contraction and deletion as two endpoints of a dimention in the conductivity space.

## 4. Decomposition on Boundary Spike

Based on the concept of contraction and deletion, now we shall be able to rewrite the formula given by lemma 2.1 to get the following result:
Theorem 4.1. Let $c$ be a boundary spike on the first boundary node in a network $\Gamma$, while $\Gamma^{C}$ and $\Gamma^{D}$ be the networks after contraction and deletion of $c$. Then we have:

$$
\begin{equation*}
\Lambda(\Gamma)=p \Lambda\left(\Gamma^{C}\right)+q \Lambda\left(\Gamma^{D}\right) \tag{2}
\end{equation*}
$$

where $p=\frac{c}{c+\Lambda\left(\Gamma^{C}\right)_{11}}, p+q=1$
Proof. In lemma 2.1 we have:
$\Lambda=\Lambda^{\prime}\left(\begin{array}{ccccc}\frac{c}{c+\Lambda_{11}^{\prime}} & -\frac{\Lambda_{12}^{\prime}}{c+\Lambda_{11}^{\prime}} & -\frac{\Lambda_{13}^{\prime}}{c+\Lambda_{11}^{\prime}} & \cdots & -\frac{\Lambda_{1 n}^{\prime}}{c+\Lambda_{11}^{\prime}} \\ & 1 & 1 & & \\ & & & & \ddots\end{array}\right]$
$=\frac{c}{c+\Lambda_{11}^{\prime}} \Lambda^{\prime}\left(\begin{array}{cccc}1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 1\end{array}\right)+\frac{\Lambda_{11}^{\prime}}{c+\Lambda_{11}^{\prime}} \Lambda^{\prime}\left(\begin{array}{ccccc}0 & -\frac{\Lambda_{12}^{\prime}}{\Lambda_{11}^{\prime}} & -\frac{\Lambda_{13}^{\prime}}{\Lambda_{11}^{\prime}} & \cdots & -\frac{\Lambda_{1 n}^{\prime}}{\Lambda_{11}^{\prime}} \\ & 1 & 1 & & \\ & & & \ddots & \\ & & & & 1\end{array}\right)$
$=\frac{c}{c+\Lambda_{11}^{\prime}} \Lambda^{\prime}+\frac{\Lambda_{11}^{\prime}}{c+\Lambda_{11}^{\prime}} \Lambda_{A}$
Notice that $\Lambda^{\prime}$ itself is just $\Lambda\left(\Gamma^{C}\right)$, and $\Lambda_{A}$ is the result of letting $C=0$ in lemma 2.1, which is also $\Lambda\left(\Gamma^{D}\right)$. Therefore we got the theorem.

For convienence, we shall call the coefficient $\frac{c}{c+\Lambda_{11}^{\prime}}$ the $p$-value of $c$ in the network $\Gamma$, denoted as $p(c ; \Gamma)$. As $c$ varies from zero to positive infinite, $p(c ; \Gamma)$ goes from 0 to 1 .

Corollary 4.2. Suppose $\Gamma, \Gamma_{1}, \Gamma_{2}$ are three networks with all the same conductances except a boundary spike, whose conductances are $c, c_{1}, c_{2}$ respectively. If $p(c ; \Gamma)=$ $k p\left(c_{1} ; \Gamma_{1}\right)+(1-k) p\left(c_{2} ; \Gamma_{2}\right)$, then we have $\Lambda(\Gamma)=k \Lambda\left(\Gamma_{1}\right)+(1-k) \Lambda\left(\Gamma_{2}\right)$.
Proof. Apply theorem 4.1.

## 5. Decomposition on Single Connection

Theorem 5.1. Let $c$ be a single connection in a network $\Gamma$, while $\Gamma^{C}$ and $\Gamma^{D}$ be the networks after contraction and deletion of $c$. Then we have:

$$
\begin{equation*}
\Lambda(\Gamma)=p \Lambda\left(\Gamma^{C}\right)+q \Lambda\left(\Gamma^{D}\right) \tag{3}
\end{equation*}
$$

where $p=\frac{c}{c+\frac{\Lambda_{1}^{A} \Lambda_{11}^{B}}{\Lambda_{11}^{B}+\Lambda_{1}^{B}}}, p+q=1$, and $\Lambda^{A}, \Lambda^{B}$ are the response matrices of the two subnetworks connected by $c$.

Proof. We shall temporarily see the conductance $c$ as two conductances $c_{A}$ and $c_{B}$ connected in series. Thus $\frac{1}{c}=\frac{1}{c_{A}}+\frac{1}{c_{B}}$. Let the vertex connecting $c_{A}$ and $c_{B}$ be $V$. Consider seperating the network into two subnetworks by cutting off the wire
at the point $V$, so that $c_{A}$ and $c_{B}$ are boudary spikes in subnetworks $\Gamma^{A}$ and $\Gamma^{B}$ respectively. Apply theorem 4.1 on each of $c_{A}$ and $c_{B}$, and wiggle the distribution of $c_{A}$ and $c_{B}$ until $p\left(c_{A} ; \Gamma^{A}\right)=p\left(c_{B} ; \Gamma^{B}\right)$. This can always be done as long as we have all-positive conductivity, because the set of equations

$$
\begin{gather*}
\frac{1}{c}=\frac{1}{c_{A}}+\frac{1}{c_{B}} \\
\frac{c_{A}}{c_{A}+\Lambda_{11}^{A}}=\frac{c_{B}}{c_{B}+\Lambda_{11}^{B}} \tag{4}
\end{gather*}
$$

always has a unique solution

$$
\begin{align*}
& c_{A}=\left(\frac{\Lambda_{11}^{A}+\Lambda_{11}^{B}}{\Lambda_{11}^{B}}\right) c \\
& c_{B}=\left(\frac{\Lambda_{11}^{A}+\Lambda_{11}^{B}}{\Lambda_{11}^{A}}\right) c \tag{5}
\end{align*}
$$

and $p(c ; \Gamma)=p\left(c_{A} ; \Gamma^{A}\right)=p\left(c_{B} ; \Gamma^{B}\right)$.
After decomposition on each part, we just "glue" back two subgraphs after contractions together, and two after deletions together, respectively. Nick Addington's work ensures the correctness of this step, see [4] p1-Lemma 1.7.

Corollary 5.2. Suppose $\Gamma, \Gamma_{1}, \Gamma_{2}$ are three networks with all the same conductances except a single connection, whose conductances are $c, c_{1}, c_{2}$ respectively. If $p(c ; \Gamma)=$ $k p\left(c_{1} ; \Gamma_{1}\right)+(1-k) p\left(c_{2} ; \Gamma_{2}\right)$, then we have $\Lambda(\Gamma)=k \Lambda\left(\Gamma_{1}\right)+(1-k) \Lambda\left(\Gamma_{2}\right)$.

Proof. Apply theorem 5.1.

## 6. A Geometric View

When we mention a response matrix space, it refers to a geometric space fromed by setting each non-trivial entry in the response matrix as a dimention. Similarly, a conductivity space means seeing each conductance in a network as a dimention. Thus the recoverability problem becomes a study on how a graph maps a conductivity space to a response matrix space. Precisely, a network (conductivity) is a point in a conductivity space, while a response matrix is a point in a response matrix space.

Consider a single connection $c$ in a network $\Gamma$. When $c$ varies from zero to positive infinite, the point $\Lambda(\Gamma)$ should moves from $\Lambda\left(\Gamma^{D}\right)$ to $\Lambda\left(\Gamma^{C}\right)$ along some path in the response matrix space. However, since $\Lambda(\Gamma)$ is a weighted average of $\Lambda\left(\Gamma^{C}\right)$ and $\Lambda\left(\Gamma^{D}\right)$, it always lies on the segement connecting these two points, which means the path is a straight line segement. This gives a geometric realization about how a single connection acts in the response matrix.

## References

[1] Curtis, Edward B. and James A. Morrow. "Inverse Problems for Electrical Networks." Series on Applied Mathematics, Vol 13; 2000.
[2] Russell, Jeff. "Recoverability of Subgraphs"; 2003.
[3] Goff, Michael. "Recovering Networks with Signed Conductivities"; 2003.
[4] Addington, Nicolas. "Stars, Eigenvalues, and Negative Conductivities"; 2003.

