

Isomorphism Between
Graphs With Distinct Eigenvalues

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1. Introduction

Two undirected graphs are said to be isomorphic if there exists a one-to-one correspondence between their nodes which preserves adjacency. There is no known polynomial time algorithm which will determine whether or not two graphs are isomorphic.

A well-known necessary condition for isomorphism is that the two graphs be cospectral (i.e., their adjacency matrices have the same set of eigenvalues). Since the eigenvalues of an $n \times n$ symmetric matrix may be computed in $O(n^3)$ time, ^{cospectral pairs of} ~~the fact that~~ nonisomorphic graphs have received much attention in the literature.

In this paper, we present an $O(n^3)$ algorithm for determining isomorphism between two cospectral n -node graphs ~~with~~ with ~~the same~~ ^{distinct} eigenvalues. In addition, we present an algorithm which completely determine the automorphism group of a graph with distinct eigenvalues in $O(n^3)$ time.

Theoretical

2. The ~~Basic~~ Framework.

Let A and B be any pair of $n \times n$ ^{nonsingular} ~~symmetric~~ ^{symmetric} cospectral matrices. Let D be the diagonal matrix consisting of the eigenvalues of A arranged on the diagonal in nondecreasing order. Let U and V be orthogonal matrices consisting of eigenvectors of A and B , respectively. ~~Arrange~~ ^{Arrange} the columns of U and V (the eigenvectors of A and B) so that $AU = UD$ and $BV = VD$. Since A and B are symmetric and nonsingular, ~~the~~ U, V and D are real matrices and may be computed in $O(n^3)$ time. ?

In addition, let P denote a permutation matrix. Note that A and B are isomorphic if and only if there exists a permutation

matrix P such that $B = P^T A P$. In the following theorem, we assume that E is a block diagonal matrix of the form

$$E = \begin{pmatrix} E_1 & & & \\ & E_2 & & \\ & & \ddots & \\ 0 & & & E_m \end{pmatrix}$$

where ^{each} E_i is orthogonal and has dimension equal to the multiplicity of the i th (when arranged in nondecreasing order) distinct eigenvalue of A .

Theorem 1: Let A, B, P, U, V and E be as described above. Then $B = P^T A P$ if and only if $U E = P V$ for some E .

Proof: By definition, we know that $A = U D U^T$ and $B = V D V^T$. Thus $B = P^T A P$

implies that $VDV^T = P^T UDU^T P$

$$\Rightarrow U^T PVD = D U^T P V.$$

Let $E = U^T P V$. Clearly $UE = PV$. Since $E D = D E$ (above), E must have the prescribed block diagonal form. E is orthogonal since U, V , and P are each orthogonal.

Conversely, assume that $UE = PV$ for some E with the prescribed ~~form~~

block diagonal form. Then $ED = DE$ and

thus $U^T PVD = D U^T P V$. Reversing

the above argument, then yields

$$B = P^T A P \quad \square$$

Theorem 1 is ^{especially} ~~particularly~~ useful when all the eigenvalues of A are different. ~~this~~

~~If the~~
 In particular, we note the following corollaries.
~~by this fact we can write several matrices~~
~~is the same as the~~
~~some of which are surprisingly strong.~~

Corollary 1: If A has n distinct eigenvalues, then $B = P^{-1}AP$ if and only if there exists a diagonal matrix E with diagonal elements ± 1 such that $AE = PV$.

Proof: The dimension of each block E_i in Theorem 1 must be 1 and since each E_i is orthogonal, $E_i^{-1} = [\pm 1]$ \square

Corollary 2: If A has distinct eigenvalues and $P \in \text{Aut}(A)$, then $P^2 = I$.

Proof: If $P \in \text{Aut}(A)$, then $A = P^{-1}AP$ and by Corollary 1, $P = UEU^T$ for some

diagonal matrix E with ± 1 's on the diagonal. Thus $P^2 = U E U^T U E U^T = U E^2 U^T = U U^T = I$ since $U U^T = I$ and $E^2 = I$. \square

Follows by Group Theory

Corollary 3: If A has distinct eigenvalues then $\text{Aut}(A)$ is abelian.
~~and $P_1, P_2 \in \text{Aut}(A)$, then~~

Proof: Given $P_1, P_2 \in \text{Aut}(A)$, we know from Corollary 1 that $P_1 = U E_1 U^T$ and $P_2 = U E_2 U^T$ where E_1 and E_2 are diagonal matrices. Thus $P_1 P_2 = U E_1 U^T U E_2 U^T = U E_1 E_2 U^T = U E_2 E_1 U^T = U E_2 U^T U E_1 U^T = P_2 P_1$ since E_1 and E_2 commute. \square

Corollary 4: If A has distinct eigenvalues

then $\sigma(\text{Mult}(A)) = 2^i$ for some $i, 0 \leq i \leq n$.

Proof: The result follows directly from Corollaries 2 and 3 \square

It is clear from corollaries 1-4 that the conditions imposed by Theorem 1 are fairly strong, particularly for the case when ~~the eigenvalues~~ ^{all the eigenvalues} of a matrix are distinct. In addition, the relation $UE = PV$ is much easier to work with ~~algorithmically than~~ ^{algorithmically than} is the associated relation $B = P^T A P$. ~~The reason~~ ^{In particular}, when all the eigenvalues of A are distinct,

$$E = \begin{pmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{pmatrix}$$
 and we will show how to solve $UE = PV$ in $O(n^3)$ time.
how do we solve $UE = PV$ for x, y, z, w

3. Restrictions on P Putting it
3.1 The Algorithm

Henceforth, we assume that A has distinct eigenvalues and that $E = \begin{pmatrix} e_1 & & 0 \\ & \ddots & \\ 0 & & e_n \end{pmatrix}$ where $e_i = \pm 1$ for $1 \leq i \leq n$. From Corollary 1, we know that $B = P^T A P$ if and only if $U E = P V$

for some such E . ~~we can concentrate~~ ~~use~~ In this section we ~~use~~ ~~use~~ this relation to partition U and V into blocks ~~and effectively characterizing these E for~~ of rows such that P must map a given block of ~~which there exists a permutation matrix P~~ rows of V into the corresponding block of rows ~~such that $U E = P V$ given any such E~~ of U , independent of the value of E . ~~then~~ ~~then~~ ~~initially found from the relation~~ ~~by reducing the matrix to the desired result~~ ~~$P^T U E = P V$~~

Define u_j to be the j th column (eigenvector) of U and v_j to be the j th column of V . Then $U E = P V$ if and only if $e_j u_j = P v_j$ for every j . Since $e_j = \pm 1$,

P must permute the rows of V so that

$$|u_i| = |v_{p(i)}|$$

the ~~with~~ row of ~~u~~

for all i, j . Thus we may partition the

rows of U and V into blocks corresponding
(of absolute values)
 to row vectors of identical magnitudes. P

must then map rows in a given block of V into

rows of the corresponding block ~~of rows~~ of U.

Such a ~~class~~ partition can be ^{easily} computed in $O(n^3)$

As an example, consider the ~~simple~~ ~~time~~ ~~and~~ ~~space~~ ~~does not involve any~~ ~~restrictions on the die.~~

As an example ~~refinement of the partition in Figure 1.~~

partitioning the matrix in Figure 1.

$$\begin{pmatrix} 1 & 1 & 2 & 3 & 4 & 0 \\ 1 & -1 & -2 & 3 & 4 & 0 \\ \hline 1 & 2 & 2 & 4 & 2 & 1 \\ -1 & 2 & 3 & 4 & 2 & 1 \\ \hline 2 & 3 & 3 & 4 & 2 & 2 \\ -2 & -3 & 3 & 4 & 2 & 3 \end{pmatrix}$$

step	partition
0	(1, 2, 3, 4, 5, 6)
1	(1, 2, 3, 4) (5, 6)
2	(1, 2) (3, 4) (5, 6)
3	(1, 2) (3) (4) (5, 6)
4	(1, 2) (3) (4) (5) (6)
5	(1, 2) (3) (4) (5) (6)
6	(1, 2) (3) (4) (5) (6)

Figure 1

Figure 1

At the i th step, we refine the previous partition to reflect information about the magnitudes of the elements in the i th column.

Once the partition according to magnitudes is complete, the magnitude of an entry need not be considered further (as all pertinent information about the magnitude is incorporated into the partition). Thus we need only know whether an entry is positive (+), negative (-) or zero (0). ~~As might be expected, the~~

~~distinction~~[†] The partition described above may be further refined through examination of the numbers of +'s and -'s in a column or a block of rows. For example, if the number of positive elements differs from the number

of negative elements in a column of a block, then that block may be divided so as to separate the positive elements from the negative elements. This is due to the fact that $e_i u_i = P v_i$ and (if u_i is a block of u_i , v_i' is the corresponding block of v_i and P' is the restriction of P to v_i') $e_i u_i' = P' v_i'$. Assume v_i' is non-zero and has x positive elements and y negative elements. ^{Then ~~the~~} ~~($e_i = 1$)~~ u_i' is non-zero and has x positive elements ($e_i = 1$) or has x negative elements ($e_i = -1$). Otherwise, A and B are immediately shown not to be isomorphic. Thus, if $x \neq y$, then the ^{x} ~~block~~ positive elements in v_i' are mapped by P into

the ^{set of} ~~to~~ ~~x~~ ~~identically~~ signed elements of u_i —
 independent of the choice of e_i (in fact,
 we ~~may~~ ^{can} determine e_i). ~~Thus, if~~ ~~both~~ ~~x~~ and ~~y~~
^(nontrivially)
 y are nonzero, then we may refine the
 partitions of U and V so that u_i and v_i
 are separated into a positive column and a
 negative column. As an illustration consider
 the refinement of the partition of the matrix

shown in ~~Figure 1~~ ⁱⁿ Figure 2.

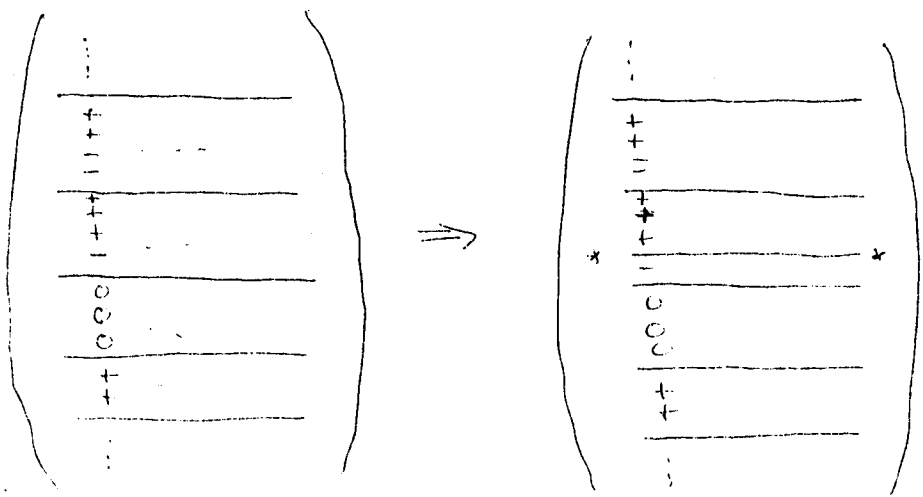


Figure 2

We may further refine the partition of U and V by inspecting the number of positive and negative elements in $v_i' \circ v_j'$ where v_i' and v_j' are non-zero columns in a block of rows and $v_i' \circ v_j'$ is the Hadamard (element-wise) product of v_i' and v_j' . This is due to the fact that $e_i e_j (u_i' \circ u_j') = p' (v_i' \circ v_j')$. Since $e_i e_j = \pm 1$, ~~the same argument~~ we may argue as before and conclude that if the number of positive elements differs from the number of negative elements in $v_i' \circ v_j'$, then we may ~~refine~~ ^{split} the ~~partition~~ ^{block} containing v_i' and v_j' into two ~~blocks~~ ^{blocks} (if $v_i' \circ v_j'$ contain both ~~positive and~~ ^{positive} and negative elements ~~table~~ ^{one otherwise})

blocks so that the ~~value~~^{sign} of $v_i' \cdot v_j'$ is uniform in each block. As an example, consider the refinement illustrated in Figure 3.

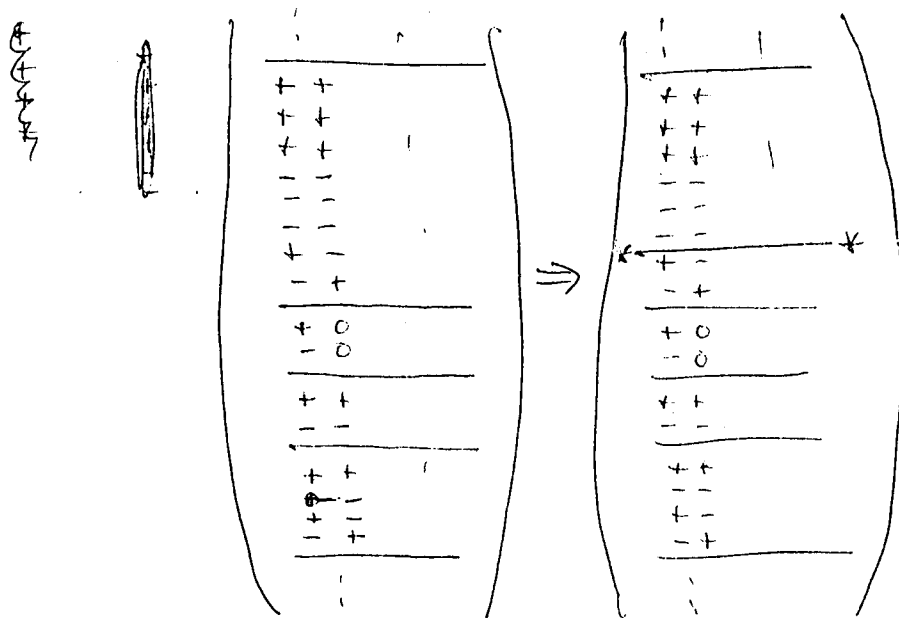


Figure 3

In general, we may refine the partition of U and V whenever there are non-zero columns v_1', \dots, v_k' in a block such that $v_1' \cdot \dots \cdot v_k'$ has unequal numbers of positive and negative

elements (and at least one of each). If we refine the partition as much as is possible by the repeated application of this procedure, then for every block and for any k non-zero columns v_1, \dots, v_k that ~~are~~ v_1, \dots, v_k in ~~the~~ block, ~~either~~ $v_1 \cdot \dots \cdot v_k$ is either uniformly signed or has an equal number of positive and negative elements. In section 5, we show that once ~~we~~ U and V are in this refined form, it will be straightforward to find all solutions to $UE = PV$. In the following section, we show how to find such a partition of U and V in $O(n^3)$ time.

4. Calculation of the Partition

Consider the following algorithm for partitioning U and V .

Algorithm 1:

Main Program

Calculate the partition according to magnitudes ~~as~~ as described in section 3. Denote the blocks B_1, \dots, B_r .

Initialize $f_{B_i}(i) \leftarrow \begin{cases} 0 & \text{if the } i\text{th column of } B_i \text{ is non-zero} \\ 1 & \text{if the } i\text{th column of } B_i \text{ is zero} \end{cases}$
for $i \in \{1, \dots, r\}$ and $i \in \{1, \dots, n\}$

Call Subroutine $(B_1, \dots, B_r, f_{B_1}(i), \dots, f_{B_r}(i))$

STOP

(Recursive) Subroutine $(B_1, \dots, B_r, f_{B_1}(i), \dots, f_{B_r}(i))$

Do 30 for $j=1, r$ (i.e. for each block)

$S \leftarrow \emptyset$

Do 20 for $i=1, n$ (i.e. for each column of the block)

(*) If $f_{B_j}(i) = 0$ for each subset $s' \subseteq S$.
 Do 10 for each subset $s' \subseteq S$ while $f_{B_j}(i) = 0$.

Calculate $w' \leftarrow v_i \cdot \prod_{s \in S'} v_s$

If w' is uniformly signed then
 set $f_{B_j}(i) \leftarrow 1$ and go to 10

If w' is unevenly signed then
 partition B_j into B_j^+ and B_j^-
 according to the signs of w'_i .
~~set $f_{B_j^+}(k) \leftarrow f_{B_j}(k)$ and $f_{B_j^-}(k) \leftarrow -f_{B_j}(k)$~~
 instead ~~set~~ $f_{B_j^+}(k) \leftarrow f_{B_j}(k)$ and $f_{B_j^-}(k) \leftarrow -f_{B_j}(k)$ for
 $1 \leq k \leq n$. Call Subroutine
 $(B_j^+, B_j^-, f_{B_j^+}(\ast), f_{B_j^-}(\ast))$. goto 30

10 CONTINUE
 20 CONTINUE
 30 CONTINUE
RETURN

Lemma 1: Algorithm 1 correctly and
 completely partitions U and V .

Proof: By induction on the number

of refinements necessary to partition the matrix.

Basis: Assume U and V are in the form described at the end of section 3 (i.e., for every block of ~~rows~~ and for any k non-zero columns v_{i_1}, \dots, v_{i_k} of that block, $v_{i_1} \cdot \dots \cdot v_{i_k}$ is either uniformly signed or has an equal number of positive and negative elements. Since Algorithm 1 only ~~works~~ splits a block when k non-zero columns ~~a refinement of the partition when~~ v_{i_1}, \dots, v_{i_k} of that block are found such that $v_{i_1} \cdot \dots \cdot v_{i_k}$ is neither uniformly signed nor contains an equal number of positive and negative elements, it is clear that Algorithm 1 works in this case.

Induction: Assume Algorithm 1 works if fewer than q ~~partitions~~ ^{refinements} of the original partition are necessary to completely partition U and V .

further assume that u and v require exactly
 q refinements. It does matter in which order
 we make the refinements so this ^{induction} is well-defined
 to completely partition. Thus, there exist
 k columns v_i^1, \dots, v_i^k ~~elements~~ of some
 block B_j such that $v_i^1 \circ \dots \circ v_i^k$ is neither
 uniformly signed nor ~~unequally~~ signed. We
 want to show that Algorithm 1 makes at least
 one refinement ~~in~~ order to apply the induction.

Assume ~~that~~ no refinement has been made.

up to the point where we ^{have} ~~are~~ examining ^{each} ~~the~~
^{columns v_i^1, \dots, v_i^k}
~~the~~ ^{columns} of the j th block B_j , ^{then} ~~we~~

^{we know} ~~that~~ that ~~there~~ for $1 \leq k \leq K$ $\exists S_k \subseteq S$ such

that $v_i^1 \circ \prod_{s \in S_k} v_i^s$ is uniformly signed (this

includes the case that $v_i^1 \in S$ since $v_i^1 \circ v_i^1$ is

trivially, uniformly signed). Thus

$$\prod_{i \in S} (v_i' \cdot \prod_{s \in S'} v_s')$$
 is uniformly signed.

The product of ^(with repetition) vectors in S is by definition

either uniformly signed or equally signed. Thus

$\prod_{i \in S} v_i'$ is uniformly ~~signed~~ or equally signed. But

this contradicts the assumption that v_1, \dots, v_n

was neither uniformly nor equally signed. Thus

Algorithm 1 makes at least one refinement and

we may apply the induction to the refined

partition.

Had there not been any reference to $(B, (i))$

~~It is clear to complete the proof, we~~
 step (*) of the previous ~~can~~ proof would now be complete.
 in the previous ~~our~~ $P \rightarrow B$ ~~vertices of~~ $P \rightarrow B$ must show that the ~~class~~ ~~which~~ ~~were~~
 since reference to the $(B, (i))$ ~~is~~ ^{essential} necessary for
~~changed before the refinement step~~

The algorithm to run quickly, we must show that

such reference does not impede the algorithm's

ability to find all possible refinements. ~~As we~~ ^{To do}

~~that~~ this we observe that $f_B(i) = 1$ for
 some block Λ^B of a refinement only if
 (i.e. before we look at Λ^B)

v_i' is all zeros or if there are k columns
 $v_{i_1}'' \dots v_{i_k}''$ of a ^{sup} block ~~containing~~ ^{B^B} of a previous partition
~~containing~~ such that $v_i' = v_{i_1}'' \cdot \dots \cdot v_{i_k}''$ is uniformly signed
 where v_{i_k}'' is the

column of B' containing v_{i_k}' and $i_1 < \dots < i_k < i$

Thus $v_{i_1}'' \cdot v_{i_2}'' \cdot \dots \cdot v_{i_k}''$ is uniformly signed in B
 ($i_1 < \dots < i_k < i$)

and, by induction, we can argue that the
 i th column need not be considered when

looking for refinements of B . \square ~~Thus completes~~

~~The proof of the theorem~~
 Lemma

In order to show that Algorithm 1
 can be executed in $O(n^3)$ time, we

must show that the set S does not grow

too large.

Lemma 2: $|S| \leq \log m$ for a block B
of m rows.

Proof: Let $S = \{v_1, \dots, v_k\}$ be a collection

of columns of a block B , such that for

any subset $S' \subseteq S$ $\prod_{v \in S'} v$ is equally

signed. Let $1 \leq j < 2^k$ denote the

k -bit binary word $j_1 j_2 \dots j_k$. Define x_j

to be number of rows such that $\prod_{v \in S} v$ has

sign $(-1)^{\sum j_\ell}$ for $1 \leq \ell \leq k$. We will show that

$x_0 = x_1 = \dots = x_{2^k-1}$, which immediately implies that

~~immediate~~ then that $|S| \leq \log m$. Note that this

is equivalent to showing that we may arrange

the rows of B so that v_1, \dots, v_k has the

form shown in Figure 4. In this illustration

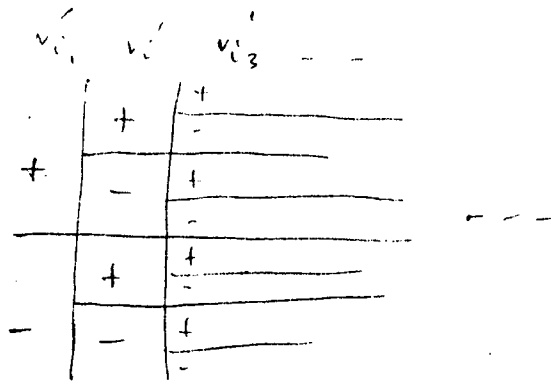


Figure 4

each subblock of signs in ^{a given} ~~each~~ column is assumed to have the same size.

By definition, the number of rows ~~for~~ ^{for} which $\sum_{s \in S} v_s^i$ is positive is $\frac{m}{2}$ for any S 's.

Thus for any $T \subseteq \{1, \dots, k\}$, $\sum_{j \in T} x_j = \frac{m}{2}$

where $T' = \{j \mid \sum_{k \in T} x_k \equiv 0 \pmod{2}\}$. In the special case when $T = \emptyset$, $T' = \{0, \dots, 2^k - 1\}$ and $\sum_{j \in T'} x_j = m$.

have ~~restrictions on~~ 2^k variables.

Since there are 2^k subsets of T , there are

2^k such restrictions on the x_j . Expressing

this information in vector notation, we have that

$$A \vec{x} = \vec{b} \quad \text{where} \quad \vec{x} = \begin{pmatrix} x_0 \\ \vdots \\ x_{2^k-1} \end{pmatrix}, \quad \vec{b} = \begin{pmatrix} m \\ m/2 \\ \vdots \\ m/2 \end{pmatrix}$$

and $A = [a_{tj}]$ where $a_{tj} = t \cdot j_1 + \dots + t_k j_{k+1} \pmod{2}$, ~~and~~ $t = t_1 \dots t_k$ and $j = j_1 \dots j_k$ are the binary representations of t and j . It is easy to show that $x_0 = x_1 = \dots = x_{2^k-1} = \frac{m}{2^k}$ is a solution of this system of equations (each row of A other than the first ~~one~~ has 2^{k-1} 1's and the rest zeroes). All that remains to be shown is that ~~$r(A) = m$~~ ^{the rank} of A , $r(A)$, is ~~2^k~~ . This is proved by induction on k . If $k=1$, then $A_1 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$ and the result is true. Assume that $r(A_{k-1}) = 2^{k-1}$ for $k \geq 2$. By observing that A_k may be easily partitioned into 4 equal sized

blocks @ $A_k = \left(\begin{array}{c|c} A_{k-1} & A_{k-1} \\ \hline A_{k-1} & J_{k-1} - A_{k-1} \end{array} \right)$ where

J_{k-1} is the $(k-1) \times (k-1)$ matrix of ones,

it is clear that:

$$r(A_k) = r \left(\left[\begin{array}{c|c} A_{k-1} & A_{k-1} \\ \hline A_{k-1} & J_{k-1} - A_{k-1} \end{array} \right] \right)$$

$$= r \left(\left[\begin{array}{c|c} A_{k-1} & A_{k-1} \\ \hline 0 & J_{k-1} - 2A_{k-1} \end{array} \right] \right)$$

~~$$= r \left(\left[\begin{array}{c|c} A_{k-1} & A_{k-1} \\ \hline 0 & 2A_{k-1} - J_{k-1} \end{array} \right] \right)$$~~

~~$$= r \left(\left[\begin{array}{c|c} A_{k-1} & A_{k-1} \\ \hline 0 & A_{k-1} \end{array} \right] \right)$$~~

$$= r \left(\left[\begin{array}{c|c} A_{k-1} & 0 \\ \hline 0 & A_{k-1} \end{array} \right] \right)$$

$$= 2 r(A_{k-1})$$

$$= 2^k \quad \text{by induction.}$$

Thus $x_0 = x_1 = \dots = x_{2^k-1} = \frac{m}{2^k}$ is the only solution

to $A_k \vec{x} = \vec{b}$ and S has the desired form \square

Lemma 3 Algorithm 1 runs in $O(n^3)$ time.

Proof: We will show by induction on the number of ^{allowable} refinements that the subroutine uses $O(m^2g)$ time to completely partition a block ^B of m rows ~~with~~ ^{with no more} ~~than~~ ^{than} g columns i such that $f_B(i) = 0$. If B is already completely refined, then the subroutine clearly verifies this in $O(m^2g)$ time. (The `do 20` loop executes ^{completely} at most g times, the `do 10` loop executes at most $2^{|S|} \leq \frac{m}{g}$ times, and it takes $O(m)$ time to calculate w' and check its signs, assuming that we store previously checked values of w'). Assume the result is true if B requires $r-1$ refinements for $r \geq 1$. Assume

that B requires r refinements. Then using the inductive hypothesis, the algorithm completely partitions B in $O(g_1 m^2 + (g_1 - g_1) m^2 + (g_1 - g_1) (m - m_1)^2)$ ~~where~~ ^{time where} g_1 is the number of columns examined before the first ~~partition~~ ^{refinement} is made and m_1 is the number of rows in ~~the~~ B^+ subblock of B . This is clearly $O(m^2 g_1)$ time and the induction is complete.

Thus the main program (which ~~part~~ ^{completely} partitions U and V) runs in $O(m^2)$ ~~time~~ ^{$O(n^3 + \sum_{j=1}^r m_j^2 n)$} where ~~the~~ $\leq O(n^3)$ ^{time} where m_j is the number of rows in the j th block of the partition according to magnitude. ~~Since~~ ^{Since} the partition by magnitude is ~~to be~~ ^{to be} complete.

5. Solutions of $UE = PV$

Once U and V are completely partitioned by Algorithm 1, it is not difficult to find all solutions (if any) to $UE = PV$. In particular, we will characterize the E 's for ~~which~~ which there is a ~~permutation~~ permutation P mapping V to UE . The permutations ~~is~~ are then easily recovered by using the relation $P = UEV^T$.

Given a completely refined block B of V and the corresponding refined block U , rearrange the rows so that the columns in S have the form shown in Figure 4. The columns which are ~~present in~~ not in S ~~are~~ are, by definition, linearly dependent on the columns in S . Thus, for every column i of B , there is a subset

~~Columns of~~ $\{v_{i_1}, \dots, v_{i_k}\} \in \mathbb{R}^n$ such
 that $v_{i_1} \cdot v_{i_2} \cdot \dots \cdot v_{i_k}$ is uniformly signed

For A and B to be isomorphic, the same
 relationship must hold for the corresponding
 columns in U (i.e. $u_{i_1} \cdot u_{i_2} \cdot \dots \cdot u_{i_k}$ is
 uniformly signed) thus we must have

~~the sign of $v_{i_1} \cdot v_{i_2} \cdot \dots \cdot v_{i_k}$~~

$\left. \begin{array}{l} \text{if } v_{i_1} \cdot v_{i_2} \cdot \dots \cdot v_{i_k} \cdot u_{i_1} \cdot u_{i_2} \cdot \dots \cdot u_{i_k} \text{ is} \\ \text{uniformly positive} \\ \text{if } v_{i_1} \cdot v_{i_2} \cdot \dots \cdot v_{i_k} \cdot u_{i_1} \cdot u_{i_2} \cdot \dots \cdot u_{i_k} \text{ is} \\ \text{uniformly negative} \end{array} \right\}$

must be shown that these restrictions
 on the e_i precisely characterize those signs
 of columns of U which permit a permutation
 of B into the corresponding block of UE . Since
 $e_i^2 = 1$, ~~these~~ ^{these} equations can be solved in ~~(e_i)~~
 time for each block of m rows.

~~The~~ In order to find the solutions to $UE=PV$,
 we must ~~then~~ determine the solutions to the
 subproblem for each block of the complete
 partition, and then compute the intersection
 of these ^{solution spaces} ~~restrictions~~. This is easily done
 in $O\left(\sum_{j=1}^k n^2 m_j + n^3\right) = O(n^3)$ time
 where the j th block has m_j rows. By
 the preceding ^{argument}, we have proved the following
~~two~~ ^{two} theorems.

Theorem 2: If A and B are ^{$n \times n$} symmetric
 matrices with distinct eigenvalues, then
 we can ^{completely} determine the α set of isomorphisms
 from B to A in $O(n^3)$ time. ~~In addition,~~
~~this set of isomorphisms may be characterized.~~

Theorem 3: ~~The~~ If A is a symmetric

matrix with distinct eigenvalues, then

$$\text{Aut}(A) = \{ P \mid P = U E U^T, E = \begin{pmatrix} e_1 & & 0 \\ & \ddots & \\ 0 & & e_n \end{pmatrix},$$

$e_1 = \pm 1, e_2 = \pm 1, \dots, e_k = \pm 1$ for some ^{sub} set of $\{i_1, \dots, i_k\} \subseteq \{1, \dots, n\}$

with $k \geq 0$ and e_{i_j} ~~is~~ ^{some fixed product} of the elements

$$\text{in } \{-1, e_1, \dots, e_{i_k}\} \quad \square$$

Note that Corollaries 1-4 also follow
trivially from Theorem 3.

6. Generalizations

Though we have not worked out the details, it appears quite likely that the preceding results can be substantially generalized to include the case when A

and B have multiple eigenvalues. ^{For example,} ~~cases~~

if ~~the maximum multiplicity of~~ ~~key step is to characterize~~ the eigenvalues of A

and B is 2, then $E = \begin{pmatrix} E_1 & & 0 \\ & \ddots & \\ 0 & & E_m \end{pmatrix}$ where each

$$E_i = \begin{bmatrix} \cos \theta & \sin \theta \\ \sin \theta & -\cos \theta \end{bmatrix} \text{ or } E_i = \begin{bmatrix} \cos \theta & \sin \theta \\ \sin \theta & -\cos \theta \end{bmatrix} \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$$

~~where~~ where $0 \leq \theta \leq 2\pi$. Thus we may

view E_i as a rotation or rotation and flip matrix.

It is then easy to describe UE in a manner

similar to that discussed in this paper.