

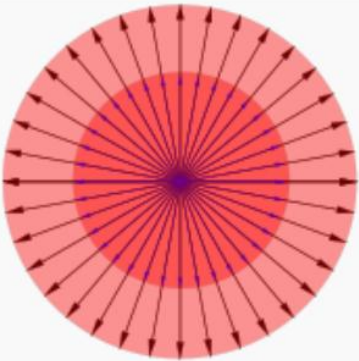
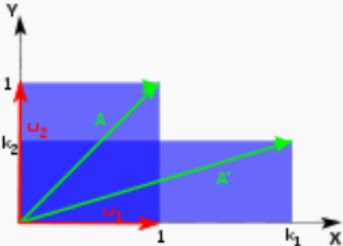
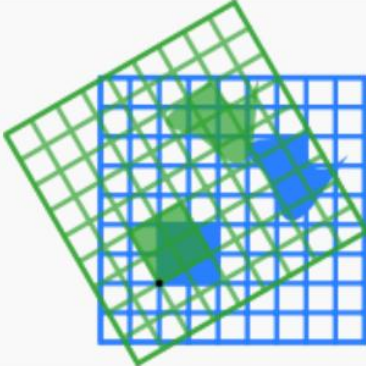
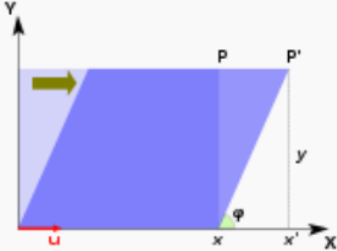


# EECS 442 – Computer vision

## Conversation hour

- Review of linear algebra
- HW 0.4 discussion
- DLT algorithm

# HW: Transformation and eigenvalues

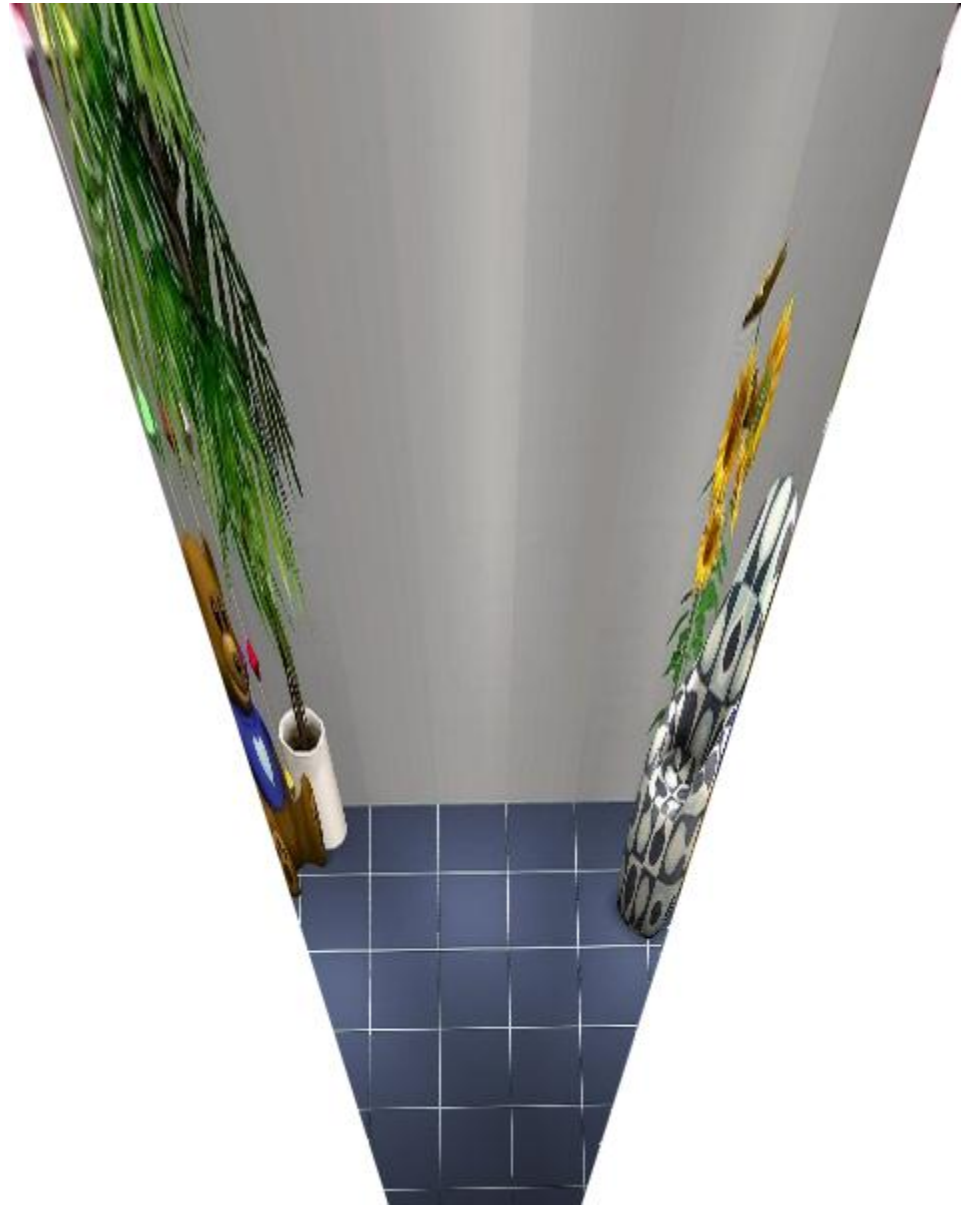
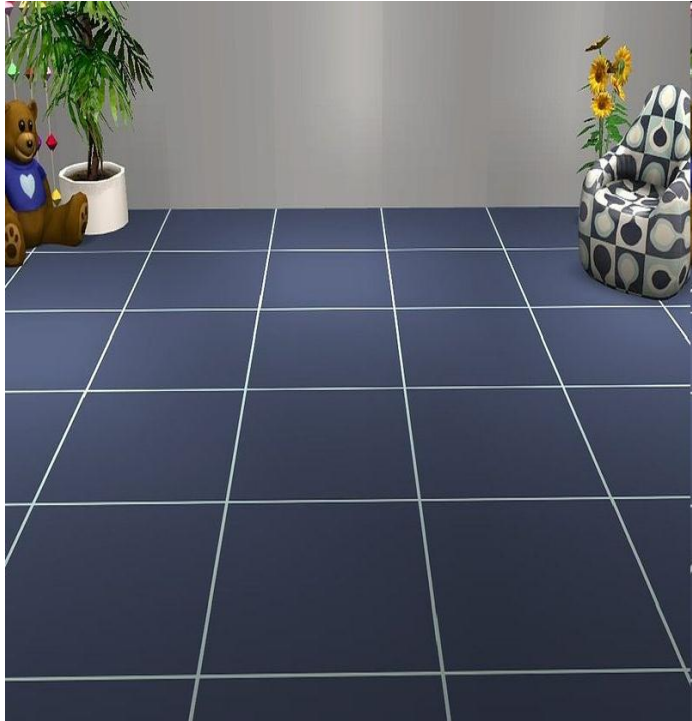
	scaling	unequal scaling	counterclockwise rotation by $\varphi$	horizontal shear
illustration				
matrix	$\begin{bmatrix} k & 0 \\ 0 & k \end{bmatrix}$	$\begin{bmatrix} k_1 & 0 \\ 0 & k_2 \end{bmatrix}$	$\begin{bmatrix} \cos \varphi & -\sin \varphi \\ \sin \varphi & \cos \varphi \end{bmatrix}$	$\begin{bmatrix} 1 & k \\ 0 & 1 \end{bmatrix}$
characteristic equation	$\lambda^2 - 2\lambda k + k^2 = (\lambda - k)^2 = 0$	$(\lambda - k_1)(\lambda - k_2) = 0$	$\lambda^2 - 2\lambda \cos \varphi + 1 = 0$	$\lambda^2 - 2\lambda + 1 = (\lambda - 1)^2 = 0$
eigenvalues $\lambda_i$	$\lambda_1 = k$	$\lambda_1 = k_1, \lambda_2 = k_2$	$\lambda_{1,2} = \cos \varphi \pm i \sin \varphi = e^{\pm i\varphi}$	$\lambda_1 = 1$
algebraic and geometric multiplicities	$n_1 = 2, m_1 = 2$	$n_1 = m_1 = 1, n_2 = m_2 = 1$	$n_1 = m_1 = 1, n_2 = m_2 = 1$	$n_1 = 2, m_1 = 1$
eigenvectors	$\mathbf{u}_1 = (1, 0), \mathbf{u}_2 = (0, 1)$	$\mathbf{u}_1 = (1, 0), \mathbf{u}_2 = (0, 1)$	$\mathbf{u}_1 = \begin{bmatrix} 1 \\ -i \end{bmatrix}, \mathbf{u}_2 = \begin{bmatrix} 1 \\ i \end{bmatrix}$	$\mathbf{u}_1 = (1, 0)$

# Removing perspective distortion

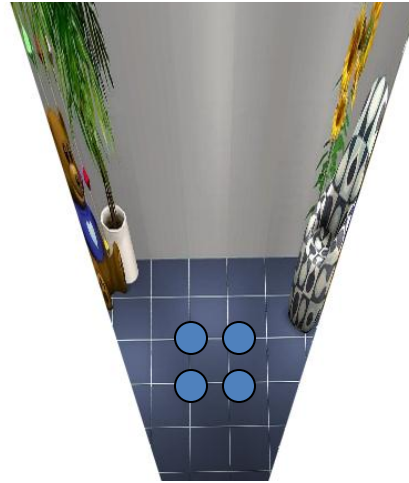
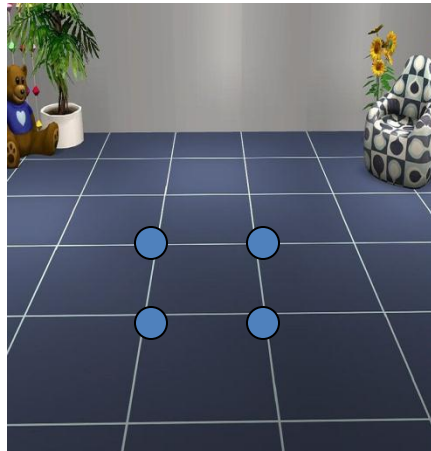
(rectification)



$H_p$



# Computing $H_p$

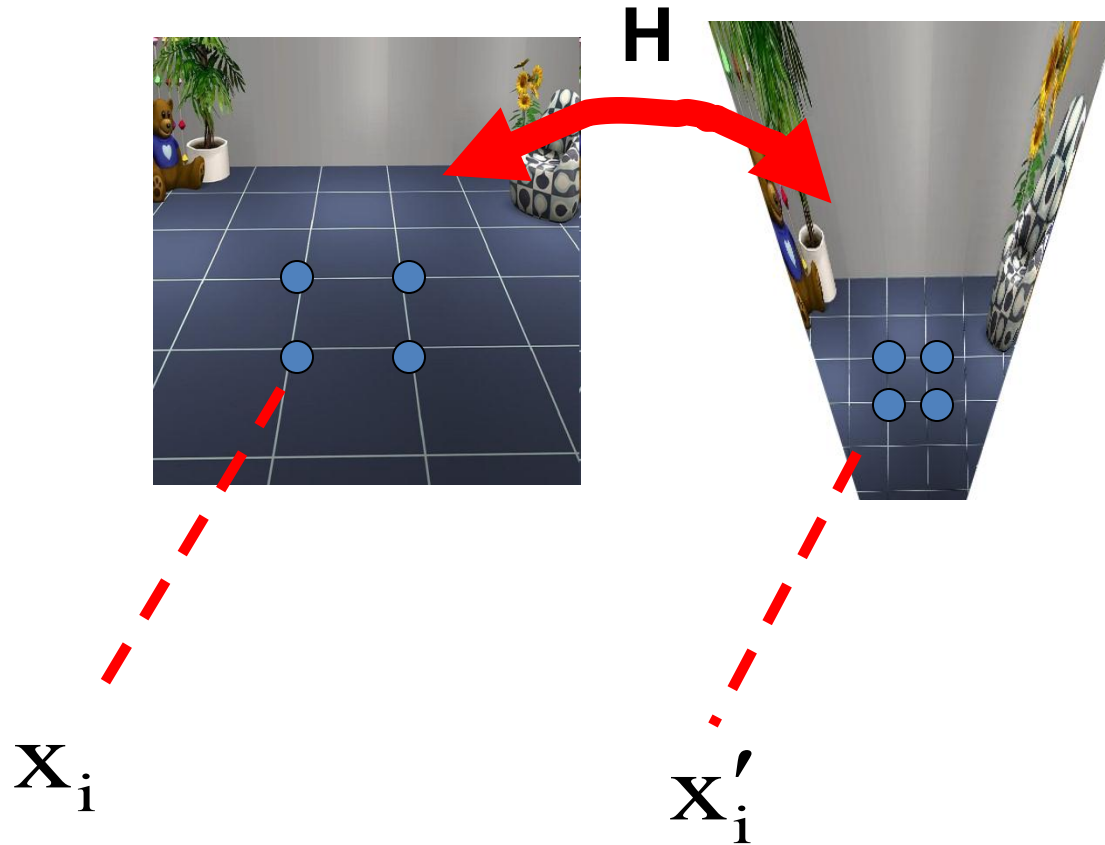


- 8 DOF
- how many points do I need to estimate  $H_p$ ?

At least 4 points! (8 equations)

- There are several algorithms...

# DLT algorithm (Direct Linear Transformation)



$$x'_i = H x_i$$

# DLT algorithm (direct Linear Transformation)

$$\mathbf{x}'_i \times \mathbf{H} \mathbf{x}_i = 0 \quad \longrightarrow \quad \underbrace{\mathbf{A}_i}_{\substack{\text{Function of} \\ \text{measurements} \quad [2 \times 9]}} \overbrace{\mathbf{h}}^{\text{Unknown } [9 \times 1]} = 0$$

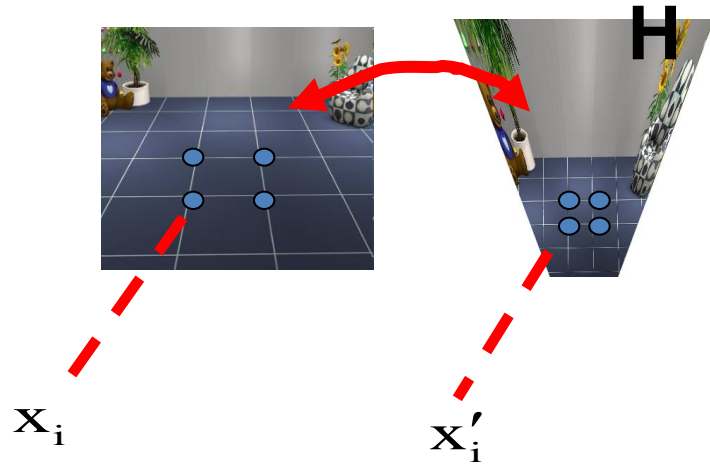
$\mathbf{h} = \underbrace{\begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_9 \end{bmatrix}}_{9 \times 1}$

$\mathbf{H} = \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix}$

2 independent equations

# DLT algorithm (direct Linear Transformation)

$$\begin{matrix} A_{2 \times 9} & h_{9 \times 1} \\ \boxed{A_i} & \boxed{h} \end{matrix} = 0$$



$$\begin{cases} A_1 h = 0 \\ A_2 h = 0 \\ \vdots \\ A_N h = 0 \end{cases} \rightarrow A_{2N \times 9} h_{9 \times 1} = 0$$

Over determined  
Homogenous system



# DLT algorithm (direct Linear Transformation)

How to solve  $\mathbf{A}_{2N \times 9} \mathbf{h}_{9 \times 1} = \mathbf{0} \quad ?$

Singular Value Decomposition (SVD)!

# DLT algorithm (direct Linear Transformation)

How to solve  $\mathbf{A}_{2N \times 9} \mathbf{h}_{9 \times 1} = \mathbf{0}$  ?

Singular Value Decomposition (SVD)!



$$\mathbf{U}_{2n \times 9} \mathbf{\Sigma}_{9 \times 9} \mathbf{V}^T_{9 \times 9}$$

Last column of  $\mathbf{V}$  gives  $\mathbf{h}$ !  $\rightarrow \mathbf{H}$ !

# DLT algorithm (direct Linear Transformation)

How to solve  $\mathbf{A}_{2N \times 9} \mathbf{h}_{9 \times 1} = \mathbf{0}$  ?

```
[U,D,V] = svd(A,0);  
x = V(:,end);
```

# Clarification about SVM

$$P_{m \times n} = U_{m \times n} D_{n \times n} V_{n \times n}^T$$

Has n orthogonal  
columns

Orthogonal  
matrix

- This is one of the possible SVD decompositions
- This is typically used for efficiency
- The classic SVD is actually:

$$P_{m \times n} = U_{m \times m} D_{m \times n} V_{n \times n}^T$$

orthogonal

Orthogonal

# Appendix:

## Properties of SVD

# Properties of the SVD

- Suppose we know the singular values of  $\mathbf{A}$  and we know  $r$  are non zero

$$\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_r \geq \sigma_{r+1} = \dots = \sigma_p = 0$$

- $\text{Rank}(\mathbf{A}) = r$ .
- $\text{Null}(\mathbf{A}) = \text{span}\{\mathbf{v}_{r+1}, \dots, \mathbf{v}_n\}$
- $\text{Range}(\mathbf{A}) = \text{span}\{\mathbf{u}_1, \dots, \mathbf{u}_r\}$
- $\|\mathbf{A}\|_F^2 = \sigma_1^2 + \sigma_2^2 + \dots + \sigma_p^2$        $\|\mathbf{A}\|_2 = \sigma_1$
- *Numerical rank*: If  $k$  singular values of  $A$  are larger than a given number  $\varepsilon$ . Then the  $\varepsilon$  rank of  $A$  is  $k$ .
- Distance of a matrix of rank  $n$  from being a matrix of rank  $k = \sigma_{k+1}$

# Why is it useful?

- Square matrix may be singular due to round-off errors.  
Can compute a “regularized” solution

– 
$$\mathbf{x} = \mathbf{A}^{-1} \mathbf{b} = (\mathbf{U} \Sigma \mathbf{V}^t)^{-1} \mathbf{b} = \sum_{i=1}^n \frac{\mathbf{u}_i^t \mathbf{b}}{\sigma_i} \mathbf{v}_i$$

- If  $\sigma_i$  is small (vanishes) the solution “blows up”
- Given a tolerance  $\varepsilon$  we can determine a solution that is “closest” to the solution of the original equation, but that does not “blow up”  
$$\mathbf{x}_r = \sum_{i=1}^k \frac{\mathbf{u}_i^t \mathbf{b}}{\sigma_i} \mathbf{v}_i \quad \sigma_k > \varepsilon, \quad \sigma_{k+1} \leq \varepsilon$$

- Least squares solution is the  $\mathbf{x}$  that satisfies  
$$\mathbf{A}^t \mathbf{A} \mathbf{x} = \mathbf{A}^t \mathbf{b}$$
- can be effectively solved using SVD

Appendix:

DLT algorithm (direct Linear Transformation)

From:

Multiple View Geometry in Computer Vision,  
by R. Hartley and A. Zisserman, Academic Press, 2002



#### 4.1 The Direct Linear Transformation (DLT) algorithm

We begin with a simple linear algorithm for determining  $H$  given a set of four 2D to 2D point correspondences,  $\mathbf{x}_i \leftrightarrow \mathbf{x}'_i$ . The transformation is given by the equation  $\mathbf{x}'_i = H\mathbf{x}_i$ . Note that this is an equation involving homogeneous vectors; thus the 3-vectors  $\mathbf{x}'_i$  and  $H\mathbf{x}_i$  are not equal, they have the same direction but may differ in magnitude by a non-zero scale factor. The equation may be expressed in terms of the vector cross product as  $\mathbf{x}'_i \times H\mathbf{x}_i = 0$ . This form will enable a simple linear solution for  $H$  to be derived.

If the  $j$ -th row of the matrix  $H$  is denoted by  $\mathbf{h}^j{}^\top$ , then we may write

$$H\mathbf{x}_i = \begin{pmatrix} \mathbf{h}^1{}^\top \mathbf{x}_i \\ \mathbf{h}^2{}^\top \mathbf{x}_i \\ \mathbf{h}^3{}^\top \mathbf{x}_i \end{pmatrix}.$$

Writing  $\mathbf{x}'_i = (x'_i, y'_i, w'_i)^\top$ , the cross product may then be given explicitly as

$$\mathbf{x}'_i \times H\mathbf{x}_i = \begin{pmatrix} y'_i \mathbf{h}^3{}^\top \mathbf{x}_i - w'_i \mathbf{h}^2{}^\top \mathbf{x}_i \\ w'_i \mathbf{h}^1{}^\top \mathbf{x}_i - x'_i \mathbf{h}^3{}^\top \mathbf{x}_i \\ x'_i \mathbf{h}^2{}^\top \mathbf{x}_i - y'_i \mathbf{h}^1{}^\top \mathbf{x}_i \end{pmatrix}.$$

Since  $\mathbf{h}^j{}^\top \mathbf{x}_i = \mathbf{x}_i^\top \mathbf{h}^j$  for  $j = 1, \dots, 3$ , this gives a set of three equations in the entries of  $H$ , which may be written in the form

$$\begin{bmatrix} \mathbf{0}^\top & -w'_i \mathbf{x}_i^\top & y'_i \mathbf{x}_i^\top \\ w'_i \mathbf{x}_i^\top & \mathbf{0}^\top & -x'_i \mathbf{x}_i^\top \\ -y'_i \mathbf{x}_i^\top & x'_i \mathbf{x}_i^\top & \mathbf{0}^\top \end{bmatrix} \begin{pmatrix} \mathbf{h}^1 \\ \mathbf{h}^2 \\ \mathbf{h}^3 \end{pmatrix} = \mathbf{0}. \quad (4.1)$$

These equations have the form  $A_i \mathbf{h} = \mathbf{0}$ , where  $A_i$  is a  $3 \times 9$  matrix, and  $\mathbf{h}$  is a 9-vector made up of the entries of the matrix  $H$ ,

$$\mathbf{h} = \begin{pmatrix} \mathbf{h}^1 \\ \mathbf{h}^2 \\ \mathbf{h}^3 \end{pmatrix}, \quad H = \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix} \quad (4.2)$$

with  $h_i$  the  $i$ -th element of  $\mathbf{h}$ . Three remarks regarding these equations are in order here.

- (i) The equation  $A_i \mathbf{h} = 0$  is an equation *linear* in the unknown  $\mathbf{h}$ . The matrix elements of  $A_i$  are quadratic in the known coordinates of the points.
- (ii) Although there are three equations in (4.1), only two of them are linearly independent (since the third row is obtained, up to scale, from the sum of  $x'_i$  times the first row and  $y'_i$  times the second). Thus each point correspondence gives two equations in the entries of  $\mathbf{h}$ . It is usual to omit the third equation in solving for  $\mathbf{h}$  ([Sutherland-63]). Then (for future reference) the set of equations becomes

$$\begin{bmatrix} \mathbf{0}^T & -w'_i \mathbf{x}_i^T & y'_i \mathbf{x}_i^T \\ w'_i \mathbf{x}_i^T & \mathbf{0}^T & -x'_i \mathbf{x}_i^T \end{bmatrix} \begin{pmatrix} h^1 \\ h^2 \\ h^3 \end{pmatrix} = 0. \quad (4.3)$$

This will be written

$$A_i \mathbf{h} = 0$$

where  $A_i$  is now the  $2 \times 9$  matrix of (4.3).

- (iii) The equations hold for any homogeneous coordinate representation  $(x'_i, y'_i, w'_i)^T$  of the point  $\mathbf{x}'_i$ . One may choose  $w'_i = 1$ , which means that  $(x'_i, y'_i)$  are the coordinates measured in the image. Other choices are possible, however, as will be seen later.
-

**Solving for H**

Each point correspondence gives rise to two independent equations in the entries of  $H$ . Given a set of four such point correspondences, we obtain a set of equations  $A\mathbf{h} = \mathbf{0}$ , where  $A$  is the matrix of equation coefficients built from the matrix rows  $A_i$  contributed from each correspondence, and  $\mathbf{h}$  is the vector of unknown entries of  $H$ . We seek a non-zero solution  $\mathbf{h}$ , since the obvious solution  $\mathbf{h} = \mathbf{0}$  is of no interest to us. If (4.1) is used then  $A$  has dimension  $12 \times 9$ , and if (4.3) the dimension is  $8 \times 9$ . In either case  $A$  has rank 8, and thus has a 1-dimensional null-space which provides a solution for  $\mathbf{h}$ . Such a solution  $\mathbf{h}$  can only be determined up to a non-zero scale factor. However,  $H$  is in general only determined up to scale, so the solution  $\mathbf{h}$  gives the required  $H$ . A scale may be arbitrarily chosen for  $\mathbf{h}$  by a requirement on its norm such as  $\|\mathbf{h}\| = 1$ .

### 4.1.2 Inhomogeneous solution

An alternative to solving for  $\mathbf{h}$  directly as a homogeneous vector is to turn the set of equations (4.3) into a inhomogeneous set of linear equations by imposing a condition  $h_j = 1$  for some entry of the vector  $\mathbf{h}$ . Imposing the condition  $h_j = 1$  is justified by the observation that the solution is determined only up to scale, and this scale can be chosen such that  $h_j = 1$ . For example, if the last element of  $\mathbf{h}$ , which corresponds to  $H_{33}$ , is chosen as unity then the resulting equations derived from (4.3) are

$$\begin{bmatrix} 0 & 0 & 0 & -x_i w'_i & -y_i w'_i & -w_i w'_i & x_i y'_i & y_i y'_i \\ x_i w'_i & y_i w'_i & w_i w'_i & 0 & 0 & 0 & -x_i x'_i & -y_i x'_i \end{bmatrix} \tilde{\mathbf{h}} = \begin{pmatrix} -w_i y'_i \\ w_i x'_i \end{pmatrix}$$

where  $\tilde{\mathbf{h}}$  is an 8-vector consisting of the first 8 components of  $\mathbf{h}$ . Concatenating the equations from four correspondences then generates a matrix equation of the form