# CSC 433/533 Computer Graphics 

## Rotations - more perspectives Transforming from one coordinate system to another

- From Linear algebra: A basis $\left\{\vec{v}_{1}, \vec{v}_{2} \ldots \vec{v}_{d}\right\}$ is a set of vectors such that every point $p$ in a space( plane/space...) could be expressed as a linear combination, $p=\alpha_{1} \cdot \vec{v}_{1}+\alpha_{2} \vec{v}_{2}+\ldots+\alpha_{d} \cdot \vec{v}_{d} \ldots$ and the scalars $\left\{\alpha_{1} \ldots \alpha_{d}\right\}$ are unique.
- The space is spanned by this basis.
- Multiplication by a matrix $M$ is a linear operation: That is
- $M \cdot \overrightarrow{0}=\overrightarrow{0}$
- $M \cdot(\vec{u}+\vec{v})=M \vec{u}+M \vec{v}$
- $M(\alpha \vec{u})=\alpha(M \vec{u})$

- We are all very familiar with the basis $\vec{X}=\binom{1}{0}$ and $\vec{Y}=\binom{0}{1}$
- For example, if $v=\binom{2}{3}$ then $v=2 \vec{X}+3 \vec{Y}$, could be understood as

Start from Origin, walk 2 meters in the $\vec{X}$ direction, followed by 3 meters in the $\vec{Y}$ direction.

## We can express rotation by creating a new basis of $\mathbb{R}^{2}$

- To specify a rotation, it is sufficient to create a new coordinates system, and specify what is the correspondence between the old and new basis.
- To be precise, create $\mathbf{M}$, such that the it's column of $\mathbf{M}$ is the $i^{\prime}$ th vector (represented as a linear combination of the basis)
- The text above is probably very cryptic without multiple examples
- "Tricky" way to find rotation matrix. If $\vec{X}, \vec{Y}$ are unit vectors in the old coordinate system, then we could think about the ro as rotating the coordinates systems as well, and after the rotation we expect
- $\vec{X} \xrightarrow[\text { by } \theta]{\text { Rotation }} \overrightarrow{X^{\prime}}$ and $\vec{Y} \xrightarrow[\text { by } \theta]{\text { Rotation }} \overrightarrow{Y^{\prime}}$. Let $R_{\theta}$ be the rotation matrix. This means: $R_{\theta} \cdot\left[\begin{array}{l}1 \\ 0\end{array}\right]=\overrightarrow{X^{\prime}} \quad$ and $\quad R_{\theta} \cdot\left[\begin{array}{l}0 \\ 1\end{array}\right]=\overrightarrow{Y^{\prime}}$.
- But $R_{\theta} \cdot\left[\begin{array}{l}1 \\ 0\end{array}\right]=\overrightarrow{X^{\prime}}$ is just the first column of $R_{\theta}$. And $R_{\theta} \cdot\left[\begin{array}{l}0 \\ 1\end{array}\right]$ is the second column.
- Lets try: Write $R_{\theta}=\left[\begin{array}{cc}\vdots & \vdots \\ \overrightarrow{X^{\prime}} & \overrightarrow{Y^{\prime}} \\ \vdots & \vdots\end{array}\right]$.
- then for every data point $C=(\alpha, \beta)$, we could write (in a somehow obnoxious way) $C=\alpha \vec{X}+\beta \vec{Y}$.
- $R_{\theta} \cdot C=\left[\begin{array}{cc}\vdots & \vdots \\ \overrightarrow{X^{\prime}} & \overrightarrow{Y^{\prime}} \\ \vdots & \vdots\end{array}\right](\alpha \vec{X}+\beta \vec{Y}) \stackrel{\text { linearity }}{=} \alpha\left[\begin{array}{cc}\vdots & \vdots \\ \vec{X}^{\prime} & \overrightarrow{Y^{\prime}} \\ \vdots & \vdots\end{array}\right] \vec{X}+\beta\left[\begin{array}{cc}\vdots & \vdots \\ \vec{X}^{\prime} & \overrightarrow{Y^{\prime}} \\ \vdots & \vdots\end{array}\right] \vec{Y}=\alpha \overrightarrow{X^{\prime}}+\beta \overrightarrow{C^{\prime}}$
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## We can express rotation by creating a new basis of $\mathbb{R}^{2}$

- This is going to be extremely useful when discussing rotations in 3 D
- To specify a rotation, it is sufficient to create a new coordinates system, and specify what is the correspondence between the old and new basis.
- To be precise, create $M$, such that the it's column of $M$ is the $i^{\prime}$ th vector (represented as a linear combination of the old basis)
- The text above is probably very cryptic without multiple examples
- "Tricky" way to find rotation matrix. If $\vec{X}, \vec{Y}$ are unit vectors in the old coordinate system, then we could think about the rotation as rotating the coordinates systems as well, and after the rotation we expect
- $\vec{X} \xrightarrow[\text { by } \theta]{\text { Rotation }} \overrightarrow{X^{\prime}}$ and $\vec{Y} \xrightarrow[\text { by } \theta]{\text { Rotation }} \overrightarrow{Y^{\prime}}$. Let $R_{\theta}$ be the rotation matrix. This means $R_{\theta} \cdot\left[\begin{array}{l}1 \\ 0\end{array}\right]=\overrightarrow{X^{\prime}}$ and $R_{\theta} \cdot\left[\begin{array}{l}0 \\ 1\end{array}\right]=\overrightarrow{Y^{\prime}}$.
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- $R_{\theta} \cdot C=\left[\begin{array}{cc}\vdots & \vdots \\ \overrightarrow{X^{\prime}} & \overrightarrow{Y^{\prime}} \\ \vdots & \vdots\end{array}\right](\alpha \vec{X}+\beta \vec{Y}) \stackrel{\text { linearity }}{=} \alpha\left[\begin{array}{cc}\vdots & \vdots \\ \overrightarrow{X^{\prime}} & \overrightarrow{Y^{\prime}} \\ \vdots & \vdots\end{array}\right] \vec{X}+\beta\left[\begin{array}{cc}\vdots & \vdots \\ \overrightarrow{X^{\prime}} & \overrightarrow{Y^{\prime}} \\ \vdots & \vdots\end{array}\right] \vec{Y}=\alpha \overrightarrow{X^{\prime}}+\beta \overrightarrow{C^{\prime}}=C^{\prime}$
- Important take home message: To find the rotation matrix, just create a matrix where each column is one of the new basis vector (written using coordinates of the old coordinate system)




## Operations on Images

Slides inspired from Fredo Durand

- Point (Range) Operations:

- Affect only the range of the image (e.g. brightness)
- Each pixel is processed separately, only depending on the color


## Operations on Images

Slides inspired from Fredo Durand

- Domain Operations:

- Only move the pixels around


## Operations on Images

Slides inspired from Fredo Durand

- Neighborhood operations:

- Combine domain and range
- Each pixel evaluated by working with other pixels nearby


# Concept for the Day: Pixels are Samples of Image Functions 



## Image Samples

- Each pixel is a sample of what?
- One interpretation: a pixel represents the intensity of light at a single (infinitely small point in space)
- The sample is displayed in such a way as to spread the point out across some spatial area (drawing a square of color)


## Continuous vs. Discrete

- Key Idea: An image represents data in either (both?) of
- Continuous domain: where light intensity is defined at every (infinitesimally small) point in some projection
- Discrete domain, where intensity is defined only at a discretely sampled set of points.


## Converting Between Image Domains

- When an image is acquired, an image is sampled from some continuous domain to a discrete domain.
- Reconstruction converts digital back to continuous.
- The reconstructed image can then be resampled and quantized back to the
 discrete domain.

```
//scale factor
let k = 4;
```


## Naive Image Rescaling Code

```
//create an output greyscale image that is both
```

//k times as wide and $k$ times as tall
Uint8Array output $=$ new Uint8Array ( $(k * W) *(k * H))$;
//copy the pixels over
for (let row $=0$, row $<\mathrm{H}$; row++) \{
for (let col = 0; col < W; col++) \{
let index = row*W + col;
let index2 = (k*row)*W + (k*col);
output[index2] = input[index];
\}
\}


## What's the Problem?

- The output image has gaps!
- Why: we skip a many of the pixels in the output.
- Why don't we fix this by changing the code to at least put some color at each pixel of the output?

```
//scale factor
let k = 4;
```


## Naive Image Rescaling Code

//create an output greyscale image that is both //k times as wide and $k$ times as tall

Uint8Array output = new Uint8Array ((k*W)*(k*H));
//copy the pixels over
for (let row $=0$, row $<\mathrm{H}$; row++) \{
for (let col = 0; col < W; col++) \{
let index $=$ row*W + col; let index2 $=(k * r o w) * W+(k * c o l) ;$ output[index2] = input[index];
\}
\}
//scale factor let $k=4$;

## "Inverse" Image Rescaling Code

//create an output greyscale image that is both //k times as wide and $k$ times as tall

Uint8Array output = new Uint8Array((k*W)*(k*H));
//Loop over each output pixel instead.

```
for (let row = 0, row < k*H; ron+4, {
```

    for (let col = 0 ; col < k*W; col++) \{
        let index \(=(\) row/k) W + (col/k);
        let index2 = row*k*W + col;
        output[index2] = input[index];
    \}
    \}


- It is nice to transform the Source image Isou and the target image Itar, both, so all pixels are in the "canonical square" $x \in[-1,1], y \in[-1,1]$.
- In general the image Is file has pixels Isou(i,j), where $i=1 \ldots N y$ (number of rows), and $j=1 \ldots N x$.


$$
b=1 / \sqrt{2} \cdot \cos \left(45^{\circ}-\operatorname{Mod}\left(\theta, 90^{\circ}\right)\right) \quad \text { ggb }
$$

$$
q^{\prime}=\text { TrSource } \overline{:::::::::}{ }^{-1} \cdot \text { ScalSource }^{-1} \cdot \text { Scale } 3 \cdot R \cdot \text { ScaTarget } \cdot \text { TrTarget } \cdot q
$$

Rotate by $\theta$ and scale by b

## Rotations in 3D

- In 2D, a rotation is about a point
- In 3D, a rotation is about an axis


2D


3D
convention: positive rotation is CCW when axis vector is pointing at you

## Rotations about 3D Axes

- In 3D, we need to pick an axis to rotate about

$$
\operatorname{rotate}-\mathrm{z}(\phi)=\left[\begin{array}{ccc}
\cos \phi & -\sin \phi & 0 \\
\sin \phi & \cos \phi & 0 \\
0 & 0 & 1
\end{array}\right]
$$

- And we can pick any of the three axes

$$
\begin{aligned}
& \operatorname{rotate}-\mathrm{x}(\phi)=\left[\begin{array}{ccc}
1 & 0 & 0 \\
0 & \cos \phi & -\sin \phi \\
0 & \sin \phi & \cos \phi
\end{array}\right] \\
& \operatorname{rotate}-\mathrm{y}(\phi)=\left[\begin{array}{ccc}
\cos \phi & 0 & \sin \phi \\
0 & 1 & 0 \\
-\sin \phi & 0 & \cos \phi
\end{array}\right]
\end{aligned}
$$

# Building Complex Rotations from Axis-Aligned Rotations 

- Rotations about $\mathbf{x}, \mathbf{y}, \mathbf{z}$ are sometimes called Euler angles
- Build a combined rotation using matrix composition



## Arbitrary Rotations

- To rotate about any axis: we change the coordinate space we are working in, using orthogonal matrices.
- Consider orthogonal matrix Ruvw, form by taking three orthogonal vectors $\mathbf{u}, \mathbf{v}$, and $\mathbf{w}$ :

Property of orthogonal vectors:
$\mathbf{u} \cdot \mathbf{u}=\mathbf{v} \cdot \mathbf{v}=\mathbf{w} \cdot \mathbf{w}=1$
$\mathbf{u} \cdot \mathbf{v}=\mathbf{v} \cdot \mathbf{w}=\mathbf{w} \cdot \mathbf{u}=\mathbf{0}$

$$
\mathbf{R}_{u v w}=\left[\begin{array}{c}
\mathbf{u} \\
\mathbf{v} \\
\mathbf{w}
\end{array}\right]
$$

## Arbitrary Rotations

- In multiple cases, we are have calculated the camera parameters, $\vec{u}, \vec{v}, \vec{w}$ and Up vectors, and want to rotate the camera, so perform a transformation a transformation taking $\vec{u} \rightarrow \vec{x}, \quad \vec{v} \rightarrow \vec{y}, \quad \vec{w} \rightarrow \vec{z} . \quad$ (Assume camera $=(0,0,0)$ )
- Technique one: compute by how much we need to rotation around each axis - very tedious.
- Technique two: Use the matrix $R_{u v w}$, where

$$
R_{u v w}=\left(\begin{array}{ccc}
- & \vec{u} & - \\
- & \vec{v} & - \\
- & \vec{w} & -
\end{array}\right)
$$

$$
\left(R_{u v w}\right)^{-1}=\operatorname{transpose}\left(R_{u v w}\right)=\left(\begin{array}{ccc}
\mid & \mid & \mid \\
\vec{u} & \vec{v} & \vec{w} \\
\mid & \mid & \mid
\end{array}\right)
$$



## Arbitrary Rotations

- What happens when we apply Ruvw to any of the basis vectors, e.g.:

$$
\mathbf{R}_{u v w} \mathbf{u}=\left[\begin{array}{l}
\mathbf{u} \cdot \mathbf{u} \\
\mathbf{v} \cdot \mathbf{u} \\
\mathbf{w} \cdot \mathbf{u}
\end{array}\right]=\left[\begin{array}{l}
1 \\
0 \\
0
\end{array}\right]=\mathbf{x}
$$

- But this means that if we apply $\mathrm{Ruvw}^{\mathrm{T}}$ (the transpose of $R_{u v w}$ ) to the Cartesian coordinate vectors, e.g.:

$$
\mathbf{R}_{u v w}^{\mathrm{T}} \mathbf{y}=\left[\begin{array}{lll}
x_{u} & x_{v} & x_{w} \\
y_{u} & y_{v} & y_{w} \\
z_{u} & z_{v} & z_{w}
\end{array}\right]\left[\begin{array}{l}
0 \\
1 \\
0
\end{array}\right]=\left[\begin{array}{c}
x_{v} \\
y_{v} \\
z_{v}
\end{array}\right]=\mathbf{v}
$$

## Recall: Vector Multiplication

- Given two 3D vectors:

$$
\mathbf{a}=\left(x_{a}, y_{a}, z_{a}\right) \mathbf{b}=\left(x_{b}, y_{b}, z_{b}\right)
$$

- So far, we've learned two forms for "multiplication":
- Dot (inner) product (2 vectors in, 1 scalar out)

$$
\mathbf{a} \cdot \mathbf{b}=x_{a} x_{b}+y_{a} y_{b}+z_{a} z_{b}
$$

- Cross product (2 vectors in, 1 vector out)

$$
\mathbf{a} \times \mathbf{b}=\left(y_{a} z_{b}-z_{a} y_{b}, z_{a} x_{b}-x_{a} z_{b}, x_{a} y_{b}-y_{a} x_{b}\right)
$$

## Determinants as Vector Multiplication

- Usually thought of as an operation on a matrix (similar to vector norms) that produces a scalar, but they can also be considered a multiplication of vectors:
- For 2d vectors $\mathbf{a}$ and $\mathbf{b}$, the determinant, |ab|, is equal to the signed area of the parallelogram formed by a and $\mathbf{b}$
- Signed here means that $|\mathbf{a b}|=-|\mathbf{b a}|$
- Related: \|a $\times \mathbf{b} \|$



## Determinants as Vector Multiplication

- For 3d vectors $\mathbf{a}, \mathbf{b}$, and $\mathbf{c}$, the determinant, |abc|, is the signed volume of the parallelepiped formed by $\mathbf{a}, \mathbf{b}$, and $\mathbf{c}$
- Sign refers to left-handed or right-handed coordinate system


