<u>**Bayes Filter for Gesture Recognition**</u>

Variables

Hidden State Space
$\mathbb{Z} = \{z_{\varnothing}^t, z_1^t, ..., z_m^t\}$
Where there are m objects and t represents the timestamp on the state.
A state consists of an object being referenced (or no object being referenced) and a timestamp.
Each state z_i^t consists of a series of 3D points.
NOTE: Consider combinations of objects? This would allow a good model of "The yellow objects". Initial model is for single objects only, but that is definitely a worthwhile extension.

Observations
$\mathbb{O} = \{o_1, ...o_t\}$
Where the subscript represents the timestamp for each observation.
Where $o_i = \{l_i, r_i, h_i, s_i\}$
Each observation consists of four parts:
l_i, the left arm vector at time i
r_i, the right arm vector
h_i, the head vector
s_i, speech
Since not all components of the observation tuple are guaranteed to be present at the same time, any of the four can take on a null value

Transition Function
The transition function $\mathbb{T}(z_i^t, z_k^{t+1})$ returns the probability of state z_i^t transitioning to z_k^{t+1}.
Transition probabilities should be high for $\mathbb{T}(z_i^t, z_k^{t+1})$ when $i = k$ and low otherwise. (Or we can start with uniform, but this makes more sense to me intuitively)
We could also weight the transition functions based on shared properties.

Let $\mathbb{N}$ represent the probability of seeing a specific sample with a normal distribution of the specified parameters, θ represent the angle between the input vector and the sample point, and w,x, and y be exponents for weighting each sample appropriately.

Equations

We wish to know the most likely state (object being referenced) given our observations and previous state estimation, namely:

$$\underset{z_i^t}{\operatorname{argmax}}[P(z_i^t|o_{t-1}) * \sum_{z_k^{t-1}\in\mathbb{Z}} P(z_i^t|z_k^{t-1})]$$

Where:

$P(z_i^t|z_k^{t-1}) = \mathbb{T}(z_k^{t-1}, z_i^t) * P(z_k^{t-1})$

$P(z_k^0) = \frac{1}{m+1}$

$P(z_i^t|o_{t-1}) = P(z_i^t|l_{t-1})^u * P(z_i^t|r_{t-1})^w * P(z_i^t|h_{t-1})^x * P(z_i^t|s_{t-1})^y$

$P(z_i^t|l_{t-1}) = \prod_{p\in z_i^t} \mathbb{N}(\mu_l = 0, \sigma_l, \theta(l_{t-1}, p))$

$P(z_i^t|r_{t-1}) = \prod_{p\in z_i^t} \mathbb{N}(\mu_r = 0, \sigma_r, \theta(r_{t-1}, p))$

$P(z_i^t|h_{t-1}) = \prod_{p\in z_i^t} \mathbb{N}(\mu_h = 0, \sigma_h, \theta(h_{t-1}, p))$

$P(z_i^t|s_{t-1}) = \text{TBD}$

NOTE: How to deal with varying cluster sizes?

1) Use only mean instead of product.

2) Pad with mean so that all clusters have the same number of particles

3) Pad with random sample so that all clusters have the same number of particles