Basketball with RFID

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Project Description

- Inspired by the HomeCourt app recently demoed at the iPhone XS release
Project Description

- Instead of machine vision like Homecourt, use wireless and RFID
- Why?
- Vision is expensive to run:
  - Camera needs to constantly be capturing, more power-hungry than RF communications
- RFID tags are cheap
RFID

- Cheap RF-based communication
  - Extremely cheap - our tags cost less than $1 per tag in bulk
- RFID antenna placed behind the backboard
- Two RFID tags, one placed on backboard, other on ball
- Tags are passive, so require no power
  - Provide minimal information, essentially only the tag’s unique ID
- Transmission distance approximately 6 meters depending on the antenna
- Operating frequency of 865 MHz
RFID (cont.)

- One single antenna, attached over USB
- Sends *interrogation* RF signals
- Tags accept, decode, and demodulate the signal
- Need enough power to do so, as well to generate, code, and modulate the response, backscatter
- Industry has stabilized around the UHF RFID standard (ISO 18000-6).
RSSI

- Received Signal Strength Indicator
- A general unit describing relative signal strength (and thus receive power)
- The RSSI coarsely corresponds to distance due to the inverse square law
- However, alone it can be ambiguous
  - No way to encode direction
Wireless Interference

- RF signals naturally interfere in the medium with each other
- Constructive & Destructive Interference
Wireless Interference Diagram

PHET Wave Interference Simulation
Innovative Finding - Tag Interference

- Choi, et. al’s Passive UHF RFID-Based Localization Using Detection of Tag Interference on SmartShelf
- Shows that RSSI is a poor indicator for localization due to multipath effects
- Key insight: Use the *interference* between two different tags to assist in localization.
- Allows localization to be done with one wide-area antenna
Baseline Data Collection

- Place ball at fixed grid positions from hoop
- Collect data for ~10 seconds from antenna
- Analyze to see if there are any trends
RSSI Topography

- Ball
RSSI
Topography 2

- Antenna
Collected Shot Diagrams

Airballs

Swishes
Collected Shot Diagrams

Bankshots
Training and Testing Data

- 403 training samples \((171/403 = 42.4\% \text{ makes})\)
- 57 testing samples \((20/57 = 40.3\% \text{ makes})\)
- 7 classifications of shots
  - Swish, Rim, Bank
  - Airball, Brick, Bankmiss, Wild
- Data Augmentation techniques
Neural Network Model

- **Convolutional Neural Network** similar to: [https://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html](https://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html)
- INPUT (128*128*3) >>> CONV (128*128*16) >>> RELU (128*128*16) >>> POOL (16*16*16) >>> CONV (16*16*20) >>> RELU (16*16*20) >>> POOL (8*8*20) >>> CONV (8*8*20) >>> RELU (8*8*20) >>> POOL (4*4*20) >>> FC (1*1*7) >>> SOFTMAX LOSS
- Max pooling
- Convolutional filter size 5*5
Neural Network Model ...continued

- Mini-Batch Size of 1
- Hyperparameters
  - Step Size = 2e-3
  - Regularization Strength = 2e-3
- Regularization strength quartered after 10,000 iterations
# Neural Network Results - Training and Testing Accuracy over Time

<table>
<thead>
<tr>
<th>Iterations</th>
<th>Training Accuracy</th>
<th>Testing Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>52.6%</td>
<td>47.4%</td>
</tr>
<tr>
<td>2000</td>
<td>60.0%</td>
<td>56.1%</td>
</tr>
<tr>
<td>5000</td>
<td>69.2%</td>
<td>59.6%</td>
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<tr>
<td>10000</td>
<td>80.4%</td>
<td>64.9%</td>
</tr>
<tr>
<td>12000</td>
<td>88.8%</td>
<td>70.2%</td>
</tr>
</tbody>
</table>
Neural Network Results

- Gradient Descent ran for 10,000 iterations
- Then 2000 iterations with different hyperparameters
- Training Set:
  - Right: 317  “Rightish”: 41
  - Wrong: 45
  - False Positive: 18 (7.8% of misses)  False Negative: 27 (15.8% of makes)
  - Absolute Accuracy: 78.7%  Real Accuracy: 88.8%
- Testing Set:
  - Right: 22  “Rightish”: 18
  - Wrong: 17
  - False Positive: 11 (29.7% of misses)  False Negative: 6 (30% of makes)
  - Absolute Accuracy: 38.6%  Real Accuracy: 70.2%
- Conclusion: Overfitting demonstrates that our idea has potential (pattern is recognizable), but we may need more training data
Notable Mispredictions

Predicted: swish
Actual: brick
Notable Mispredictions

Predicted: rim
Actual: brick
Notable Mispredictions

Predicted: wild
Actual: bank
Flaws with Our Project

- CNN overfitting
- Perhaps RNN or LTSM would have worked better than a CNN
- Unbalanced data set
- Maybe not enough training samples (not even a validation set!)
- Really bad basketball hoop (rim not similar to professional rim)
  - Put GIF here
- Hard to distinguish a missed shot from “not a shot”
Alternatives and Future Work

- Use ambient backscatter to avoid needing to power an antenna behind every basketball hoop
  - Utilizes background wireless signals such as TV, WiFi to transmit data
- Automated system to get more training data
- More RFID tags on ball and around the basketball hoop.
- More antennas
- Longer training on neural network, tweak of hyperparameters
- Better positioning of the antenna RFID tag to take better advantage of interference patterns
Conclusions

- Accurate RFID localization is very hard
- Many proposed solutions for RFID localization have inaccuracies that prevent them from solving this particular problem
Questions?
References