

Spatial Model and Coordinate Systems

Phase 5: 3D Reconstruction & Field Reference Frame

This document describes the 3D reconstruction pipeline, coordinate systems, and spatial modeling for the Rugby Vision system.

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Overview

Phase 5 transforms 2D detections and tracks from Phase 4 into 3D positions in a rugby field coordinate system. The pipeline consists of:

1. **Camera Calibration:** Load intrinsic and extrinsic parameters for each camera
2. **Triangulation:** Reconstruct 3D points from multi-view 2D observations
3. **Field Coordinate Transform:** Map 3D points into rugby field reference frame
4. **Frame State Generation:** Build time series of ball and player positions

Key Components

- `ml/calibration.py` : Camera calibration data structures and loading
 - `ml/triangulation.py` : Multi-view triangulation (DLT method)
 - `ml/field_coords.py` : Rugby field coordinate system definition
 - `ml/spatial_model.py` : Integration and frame state generation
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Coordinate Systems

1. Camera Coordinates (OpenCV Convention)

Each camera has its own local coordinate system:

A diagram showing the camera coordinate system. A vertical line points upwards and is labeled 'Y (down)'. A horizontal line points to the right and is labeled 'X (right)'. A diagonal line points down and to the left, labeled 'Z (forward, into scene)'.

- **Origin:** Camera optical center
- **X-axis:** Right (in image plane)
- **Y-axis:** Down (in image plane)
- **Z-axis:** Forward (depth, into the scene)

2. World Coordinates (Rugby Field)

Global 3D coordinate system aligned with the rugby field:

A diagram showing the world coordinate system for a rugby field. A vertical line points upwards and is labeled 'Z (up)'. A horizontal line points to the right and is labeled 'X (touchline)'. A diagonal line points down and to the left, labeled 'Y (field length)'. The diagram also shows 'Try Line 0' and 'Try Line 1' on the left and right sides respectively.

- **Origin:** Corner of try line (left corner when viewing from field center)
- **X-axis:** Along touchline (0 to 70m)
- **Y-axis:** Along field length (0 to 100m)
- **Z-axis:** Vertical, upward (0 = ground level)

3. Image/Pixel Coordinates

2D coordinates in camera images:

A diagram showing the 2D image/pixel coordinate system. A horizontal line points to the right and is labeled 'X (width)'. A vertical line points downwards and is labeled 'Y (height)'. The origin is labeled '(0,0)' at the top-left corner. The bottom-right corner is labeled '(1920, 1080)'. The bottom-left corner is labeled '(0,1080)'.

- **Origin:** Top-left corner of image
- **X-axis:** Image width (pixels)
- **Y-axis:** Image height (pixels)

Camera Calibration Model

Intrinsic Matrix

The intrinsic matrix **K** (3×3) contains internal camera parameters:

$$K = \begin{bmatrix} f_x & 0 & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix}$$

Parameters:

- f_x , f_y : Focal lengths in pixels (X and Y directions)
- c_x , c_y : Principal point (optical center) in pixels

Typical values for 1920×1080 camera:

- f_x , f_y : 1400-1600 (narrower FOV) or 800-1200 (wider FOV)
- c_x : ~960 (half of image width)
- c_y : ~540 (half of image height)

Extrinsic Matrix

The extrinsic matrix **[R|t]** (4×4) transforms world points to camera coordinates:

$$[R|t] = \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Components:

- **R** (3×3): Rotation matrix (orthogonal, $\det(R) = 1$)
- **t** (3×1): Translation vector (camera position in world coords)

Projection Matrix

The full projection matrix **P** (3×4) maps 3D world points to 2D image points:

$$P = K [R|t]$$

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \sim P \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

Where \sim denotes equality up to scale (homogeneous coordinates).

Validation

The system validates calibration parameters:

- ☒ Intrinsic matrix is 3×3 with bottom row [0, 0, 1]
- ☒ Focal lengths are positive
- ☒ Extrinsic matrix is 4×4 with bottom row [0, 0, 0, 1]
- ☒ Rotation matrix is orthogonal: $R \times R^T = I$

Triangulation Method

Direct Linear Transform (DLT)

We use the **Direct Linear Transform** method for multi-view triangulation.

Problem Formulation

Given:

- $N \geq 2$ calibrated cameras
- 2D observations (u_i, v_i) in each camera i

Find:

- 3D point $X = [X, Y, Z]^T$ in world coordinates

Algorithm

1. **Build Linear System:** For each observation (u, v) in camera with projection matrix P :

$$\begin{aligned} u \times P[2, :] - P[0, :] &= 0 \\ v \times P[2, :] - P[1, :] &= 0 \end{aligned}$$

This gives us matrix equation: $A \times X_h = 0$ where $X_h = [X, Y, Z, 1]^T$

1. **Solve via SVD:** The solution is the right singular vector corresponding to the smallest singular value:

$$\begin{aligned} A &= U \Sigma V^T \\ X_h &= V[:, -1] \quad (\text{last column of } V) \end{aligned}$$

1. **Convert to 3D:** Divide homogeneous coordinates by the 4th component:

$$X = X_h[0:3] / X_h[3]$$

Reprojection Error

To validate triangulation quality, we compute reprojection error:





$$\text{error}_i = \sqrt{(u_i - u_{\text{proj}_i})^2 + (v_i - v_{\text{proj}_i})^2}$$

where $(u_{\text{proj}_i}, v_{\text{proj}_i})$ is the projection of X back into camera i .

Threshold: We reject reconstructions with max error > 100 pixels.

Edge Cases

The triangulation function handles:

-  Fewer than 2 observations \rightarrow ValueError
-  Degenerate geometry ($\text{rank}(A) < 3$) \rightarrow return None
-  Point at infinity ($X_h[3] \approx 0$) \rightarrow return None
-  High reprojection error \rightarrow return None

Rugby Field Reference Frame

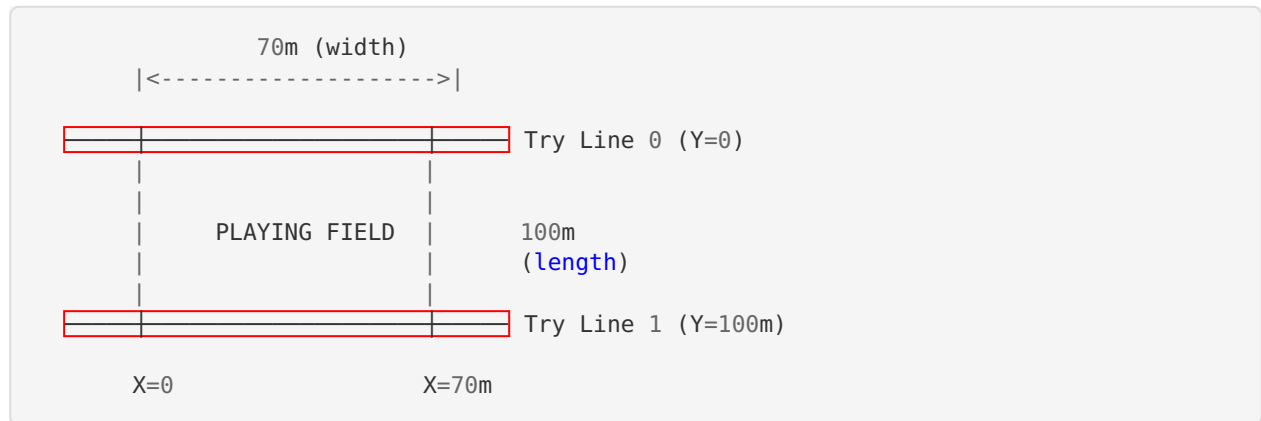
Field Model

The `FieldModel` dataclass defines rugby field dimensions and the coordinate transform:

```
@dataclass
class FieldModel:
    field_length: float = 100.0 # Try line to try line (m)
    field_width: float = 70.0 # Touchline to touchline (m)
    try_line_0: float = 0.0 # First try line Y-coord
    try_line_1: float = 100.0 # Second try line Y-coord
    origin_offset: np.ndarray # World origin to field origin
    rotation_matrix: np.ndarray # 3x3 rotation to field coords
```

Standard Dimensions

Rugby field dimensions follow World Rugby regulations:



Coordinate Transform

To transform a 3D point from world to field coordinates:

```
field_point = R @ (world_point - offset)
```

Where:

- `R` : Rotation matrix (3×3)
- `offset` : Translation vector (3×1)

Validation

Field coordinate validation:

- ☒ **Z ≥ 0**: Points must be at or above ground level
- ☒ **Bounds checking**: Points should be within field dimensions (with tolerance)
- ☒ **Reasonable height**: $Z < 50\text{m}$ (sanity check)

Tolerance: Default 5m for out-of-bounds plays (e.g., throw-ins)

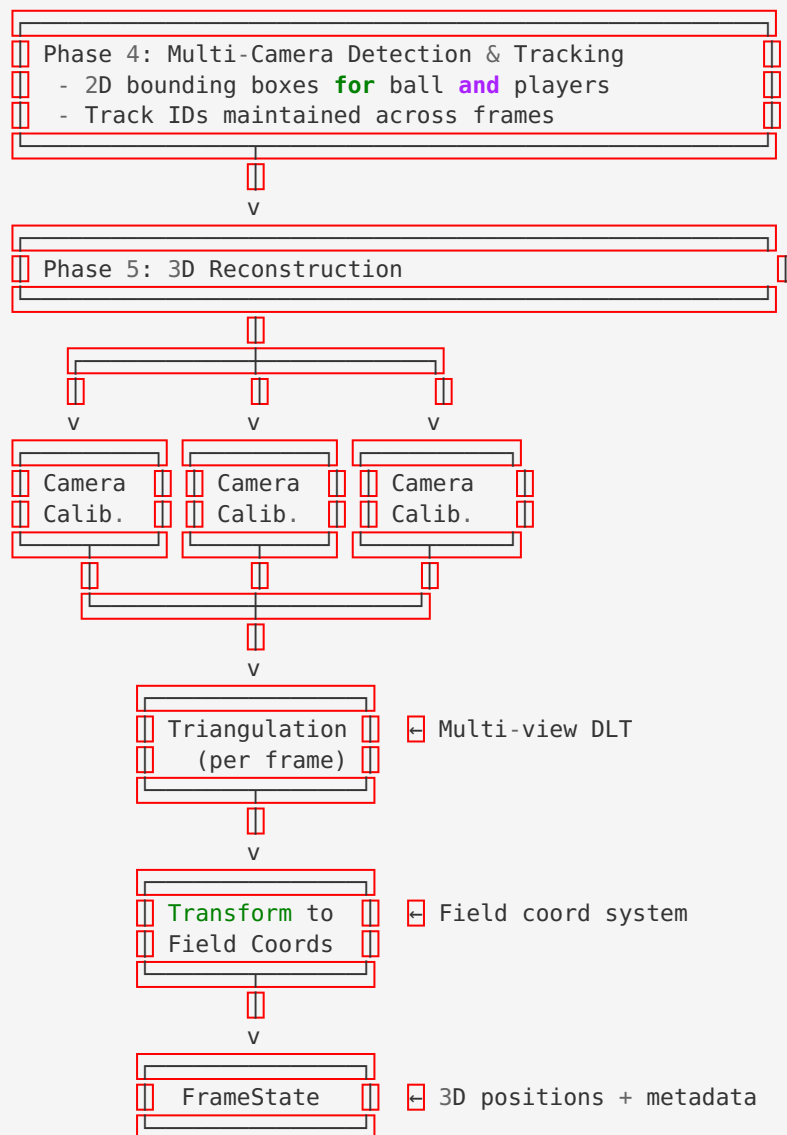
Spatial Model Pipeline

FrameState Data Structure

Each frame's spatial state is captured in:

```
@dataclass
class FrameState:
    timestamp: float           # Frame timestamp (seconds)
    frame_number: int          # Frame index
    ball_pos_3d: Optional[np.ndarray] # Ball position [X, Y, Z] or None
    players_pos_3d: Dict[int, np.ndarray] # track_id -> [X, Y, Z]
    ball_detected: bool        # Whether ball was detected
    n_players_tracked: int      # Number of players in 3D
```

Pipeline Steps



Ball Position Reconstruction

For each frame:

1. **Collect observations:** Find ball detections across all cameras
2. **Select best detection:** Use highest confidence if multiple balls detected per camera
3. **Get pixel coordinates:** Center of bounding box (x_{center} , y_{center})
4. **Triangulate:** Apply DLT with ≥ 2 observations
5. **Transform:** Map to field coordinates
6. **Validate:** Check $Z \geq 0$ and reasonable bounds

Player Position Reconstruction

For each tracked player (per track_id):

1. **Match tracks:** Find same track_id across cameras
2. **Get pixel coordinates:** Bottom-center of bounding box (feet position)
3. **Triangulate:** Apply DLT with ≥ 2 observations
4. **Transform:** Map to field coordinates
5. **Validate:** Check $Z \geq 0$ and field bounds

Note: Players use bottom-center of bounding box (feet) while ball uses center.

Error Handling

Guard Clauses

Following project coding standards, we use guard clauses for validation:

```
# Insufficient cameras
if len(observations) < 2:
    raise ValueError("Need at least 2 observations for triangulation")

# Degenerate geometry
if np.linalg.matrix_rank(A) < 3:
    return None # Cannot solve





# Point below ground
if field_point[2] < -0.1:
    return None # Invalid position
```

Missing Data Handling

Scenario	Handling
Ball not detected in frame	<code>ball_pos_3d = None</code> , <code>ball_detected = False</code>
Ball detected in <2 cameras	Cannot triangulate → <code>ball_pos_3d = None</code>
Player track in <2 cameras	Skip this player for this frame
High reprojection error	Reject triangulation → return None
Invalid field coordinates	Return None, skip this detection

Logging

Key events are logged:

-  Calibration file loaded successfully
-  Triangulation failed (degenerate geometry)
-  Point rejected (high reprojection error)
-  Point rejected (invalid field coordinates)

Future Improvements

Phase 6: Temporal Filtering

- **Kalman filtering:** Smooth 3D trajectories over time
- **Velocity estimation:** Compute ball/player velocities
- **Occlusion handling:** Predict positions during missing detections
- **Outlier rejection:** Use temporal consistency to filter bad reconstructions

Phase 7: Advanced Calibration

- **Online calibration refinement:** Use field lines for continuous calibration
- **Rolling shutter correction:** Account for camera sensor effects
- **Lens distortion:** Model and correct radial/tangential distortion
- **Auto-calibration:** Recover calibration from video alone (structure-from-motion)

Phase 8: Decision Engine

- **Forward pass detection:** Use ball 3D trajectory + player positions
- **Pass direction computation:** Analyze ball velocity and player orientations
- **Rule violations:** Detect offside, knock-ons, etc.
- **Confidence scoring:** Probabilistic decision making

Performance Optimization

- **Batch triangulation:** Vectorize operations for multiple points
- **GPU acceleration:** Use CUDA for projection matrix operations
- **Multi-threading:** Parallelize per-frame reconstruction
- **Caching:** Store projection matrices to avoid recomputation

Robustness Improvements

- **RANSAC triangulation:** Reject outlier observations
- **Bundle adjustment:** Jointly optimize 3D points and camera poses
- **Multi-hypothesis tracking:** Handle track ID ambiguities
- **Uncertainty quantification:** Estimate 3D position covariance

References

1. **Hartley, R. & Zisserman, A.** (2004). Multiple View Geometry in Computer Vision. Cambridge University Press.
- Chapter 12: Structure Computation (DLT triangulation)
 2. **OpenCV Documentation.** Camera Calibration and 3D Reconstruction.
- https://docs.opencv.org/4.x/d9/d0c/group__calib3d.html
 3. **World Rugby.** Laws of the Game - Rugby Union.
- Field dimensions and regulations
-

Appendix: Code Examples

Loading Calibration

```
from ml.calibration import load_calibration_from_file

calibrations = load_calibration_from_file('config/camera_calibration_example.json')
# Returns: Dict[camera_id, CameraCalibration]
```

Triangulating a Point

```
from ml.triangulation import triangulate_point

observations = [
    (calibrations['cam_0'], (640.5, 480.2)),
    (calibrations['cam_1'], (1024.1, 512.7)),
    (calibrations['cam_2'], (800.0, 600.0)),
]

point_3d = triangulate_point(observations) # Returns [X, Y, Z] or None
```

Transforming to Field Coordinates

```
from ml.field_coords import transform_to_field_coords, get_standard_rugby_field

field_model = get_standard_rugby_field()
field_point = transform_to_field_coords(point_3d, field_model)
# Returns [X_field, Y_field, Z_field] or None
```

Building Frame States

```
from ml.spatial_model import build_frame_states

frame_states = build_frame_states(
    tracking_results=tracking_results, # Dict[camera_id, DetectionTrackingResult]
    calibrations=calibrations,        # Dict[camera_id, CameraCalibration]
    field_model=field_model,          # FieldModel
    fps=30.0                          # Frames per second
)

# Returns List[FrameState]
```

Document Version: 1.0

Last Updated: Phase 5 Implementation

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