Extraction and analysis of 3D kinematic parameters of Table Tennis ball from a single camera

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ICPR 2020

10-15 January 2021 - Milan, Italy

Context

- Human pose estimation and video recognition are popular areas of research in computer vision
- Gesture analysis often restricted to laboratory experiments
- Ball trajectory in Table Tennis = quality indicator of a stroke
- Goal : Help teachers, coaches, players with few acquisitions constraints
  - Extract ball 3D position with a single camera
  - Ball kinematics information (speed, rotation ...)

Figure – Acquisition of Table Tennis video sequences

Net Forces

$$m\boldsymbol{a} = m\frac{d\boldsymbol{V}}{dt} = \boldsymbol{F}_G + \boldsymbol{F}_D(\boldsymbol{V}) + \boldsymbol{F}_L(\boldsymbol{V})$$

List of forces :

- **Gravity** F_G

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List of forces :

- Gravity F_G
- **Drag effect** : F_D = Frictional force opposite to the relative motion of the ball

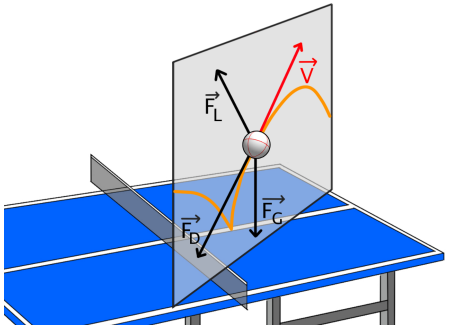

Figure – Forces applied on the ball (black) and ball velocity vector (red)

Net Forces

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List of forces :

- Gravity F_G
- Drag effect : F_D = Frictional force opposite to the relative motion of the ball
- **Lift (Magnus Effect[1,2])** F_L = Difference of air pressure on the upper and lower sides of the ball due to the rotating on itself

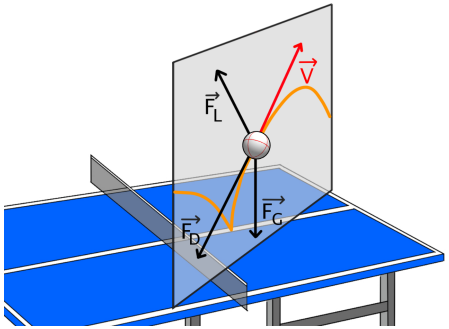

Figure – Forces applied on the ball (black) and ball velocity vector (red)

[1] T. Miyazaki, et al. European Journal of Physics, 38(2) :024001, dec 2016
[2] R. Schneider et al. Statistical analysis of table-tennis ball trajectories. Applied Sciences,8 :2595, 12 2018

Ball trajectory analysis

3D Position Estimation

Steps of our approach to estimate the 3D ball position :

- Ball Detection even with high motion blured (Detectron2[1])
- Initialize tracker CSRT[2]
- Split the trajectory in piecewise curves (impact detection)

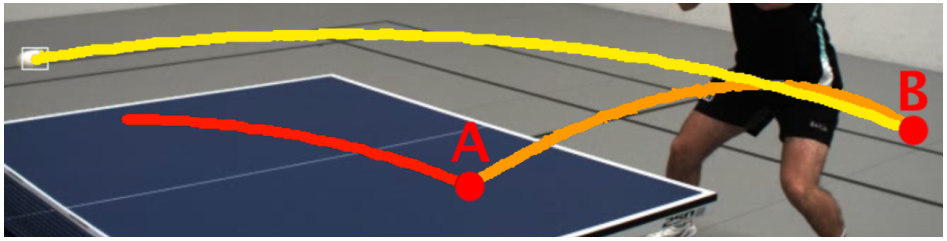

Figure – Piecewise trajectory of a ball during a match

[1] Ross Girshick, Ilija Radosavovic, Georgia Gkioxari, Piotr Dollà, and Kaiming He. Detectron, https ://github.com/facebookresearch/detectron, 2018.
[2] Alan Lukezic, Tomas Vojir, Luka Cehovin Zajc, Jiri Matas, and Matej Kristan. Discriminative correlation filter with channel and spatial reliability. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), July 2017.

3D Position Estimation

Steps of our approach to estimate the 3D ball position :

- Ball Detection even with high motion blured (Detectron2)
- Initialize tracker CSRT
- Split the trajectory in piecewise curves (impact detection)
- For each frame of the trajectory part of interest :
  - Spacio-temporal cube of size 128x128x5 centered on the ball position
  - Input the frames to a CNN to obtain the observed ball size
  - Deduce the Camera-Ball distance using intrinsic camera matrix

Dataset

Assumption : ball trajectory lies in a plane for the selected stroke

Real Dataset
- Four different players
- 29 sequences
- Two high speed synchronized cameras (240 fps)
- 3D Position Ground Truth using triangulation
- No rotation speed or translation speed Ground Truth

Figure – Representation frames of a `Top Spin` (left), a `Counter Attack` (center) and a `Push` (right)

Synthetic Dataset
- Blender Software, rendered with Cycles[1]
- Scene synthesized using camera matrices (table position, camera positions ...)
- 200 synthetic sequences
- 30807 frames
- Rotation speed, translation speed and 3D position Ground Truth
- Motion blur simulation

Figure – Real motion blur (left) and generated frame (right)

[1] `https://docs.blender.org/manual/en/latest/render/cycles/index.html`

Results

3D position estimation

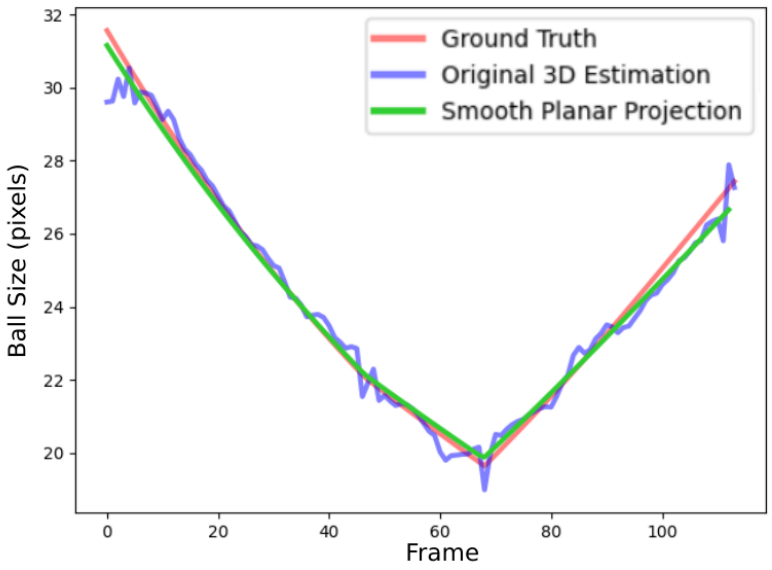

Figure – Ball size estimation results

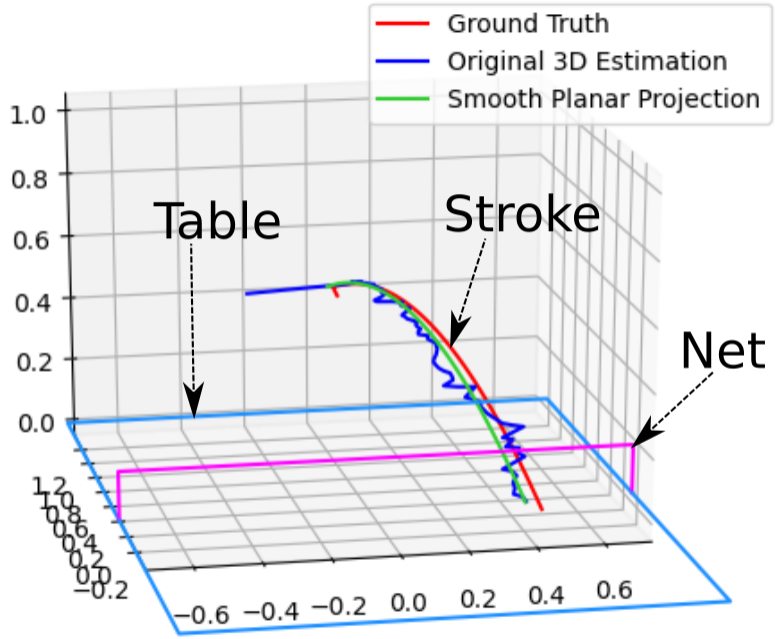

Figure – Ball retro-projection

Stroke	3D Error	Planar Error
Top Spin	6.43	4.28
Counter attack	5.84	3.86
Push	5.27	3.52

Table – Average quadratic error between the real and estimated 3D position of the ball (in cm)

Results

Extracted translation and rotation speeds

Stroke	Translation (m/s)	Rotation (cps)
Top Spin	0.75	4.48
Counter attack	0.16	2.70
Push	0.09	0.99
Global	0.41	3.04

Table – Average estimated error of the extracted parameters for each of the three stroke types

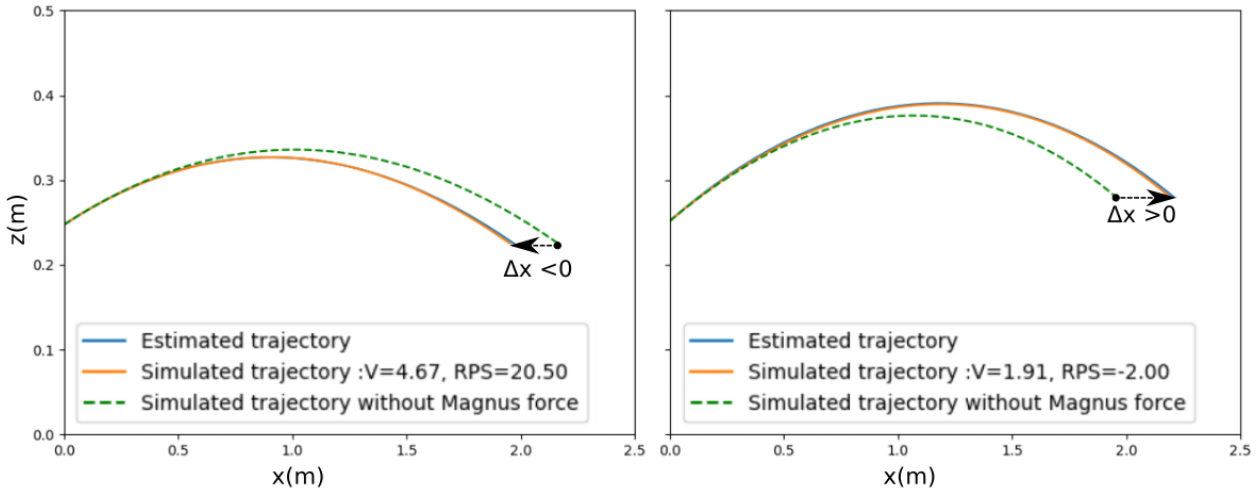

Figure – Comparison between estimated trajectories with and without Magnus effect on `Counter Attack` (left) and `Push` (right) strokes

Action Recognition based on ball speeds

On real life training set

- 20 sequences for fine-tuning
- 9 sequences for test (3 of each stroke)
- Naive Bayes Classifier => 100% classif

Name	Speed (m/s)	Rotation per sec.	Ground truth	Naive Bayes Prediction		
				TS	Counter	Push
Seq. 1	13.00	38.50	Top Spin	**1.00**	0.00	0.00
Seq. 2	14.00	32.50	Top Spin	**1.00**	0.00	0.00
Seq. 3	13.00	32.00	Top Spin	**1.00**	0.00	0.00
Seq. 4	10.00	10.00	Counter	0.03	**0.97**	0.00
Seq. 5	9.80	9.50	Counter	0.00	**1.00**	0.00
Seq. 6	9.00	9.00	Counter	0.00	**1.00**	0.00
Seq. 7	5.00	-15.00	Push	0.00	0.00	**1.00**
Seq. 8	4.80	-13.50	Push	0.00	0.00	**1.00**
Seq. 9	5.00	-14.00	Push	0.00	0.00	**1.00**

Table – Classification results from extracted kinematic parameters on the real dataset

Future works and prospects

- Assumption : trajectory lies in a plane
  - True for the 3 considered stroke types used
  - Side spins can be strong for other stroke types
  - => Take sidespin into account to expand the number of classes
- Use of a larger dataset with more stroke types
- MediaEval 2021 (Classification of Strokes in Table Tennis Workshop)

Thank you for your attention !