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Data Article

A comprehensive handball dynamics dataset for game situation classification

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ABSTRACT

This article presents a comprehensive dataset of labeled game situations obtained from multiple professional handball matches, which corresponds to the research paper entitled “PlayNet: Real-time Handball Play Classification with Kalman Embeddings and Neural Networks” [1]. The dataset encompasses approximately 11 hours of footage from five handball games played in two different arenas, resulting in around 1 million data frames. Each frame has been meticulously labeled using seven distinct game situation classes (left and right attacks, left and right transitions, left and right penalties, and timeouts). Notably, the dataset does not contain video frames, but provides a synthetic normalized representation of each frame. This representation includes information about player, referee, and ball positions, as well as player and referee velocities, for every labeled game situation. We obtained said details automatically by using an object detector to infer the positions of players, referees, and the ball in each frame. After tracking the detected agent positions across frames, the extracted coordinates underwent normalization through a “bird’s eye” perspective transform, ensuring that the data remained unaffected by variations in camera configurations across different arenas. Finally, a Kalman filter was applied to improve the robustness of player po-

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sitions and derive their velocities. The labeling process was performed by domain experts employing a custom system designed to annotate game situations, considering the play type and its contextual setting. In conclusion, researchers can utilize this dataset for several purposes: game analysis, automated broadcasting, or game summarization. Furthermore, this dataset can contribute to a broader understanding of the relationship between player dynamics and game situations, shedding light on the level of granularity required for accurately classifying them.

Specifications Table

Subject	Data Science / Applied Machine Learning
Specific subject area	Handball game situation classification (the process of obtaining the type of play for a certain moment of a handball match). Similar terms: play classification, play recognition.
Data format	Analyzed Filtered (Note: Raw data was analyzed and filtered to obtain robust positions and velocities using a Kalman filter).
Type of data	.csv file (player, referee, and ball data for the train split) .csv file (game situations for the train split) .csv file (player, referee, and ball data for the test split) .csv file (game situations for the test split)
Data collection	A static two-camera setup was installed in each venue (2 x AXIS P1468 and 2 x AXIS M1125) to record handball matches. The 5 recorded matches took place in two Spanish sports facilities between February 2019 and September 2020. The captured videos were subsequently processed using an object detector (YOLOv4), a tailor-made object tracker, and a Kalman filter to extract normalized court positions and velocities (accounting for perspective distortion) for each game agent. The processing was performed in the cloud, in a G4 AWS instance. Lastly, field experts utilized custom labeling software to manually classify the game frames.
Data source location	Institute: Universidade da Coruña City/Town/Region: A Coruña Country: Spain
Data accessibility	Repository name: Zenodo Data identification number: 10.5281/zenodo.8220670 Direct URL to data: https://doi.org/10.5281/zenodo.8220670
Related research article	O.A. Mures, J. Taibo, E.J. Padrón, J.A. Iglesias-Guitian, PlayNet: real-time handball play classification with Kalman embeddings and neural networks, Vis. Comput. (2023). https://doi.org/10.1007/s00371-023-02972-1.

1. Value of the Data

- These data can be beneficial for creating and assessing machine learning models and data analysis algorithms related to handball. Moreover, it can provide valuable insights into how player dynamics contribute to specific play situations. Furthermore, as far as we know, this is the largest publicly accessible handball play classification dataset.
- Experimentation in artificial intelligence and data analysis can utilize this dataset to extract relevant data and uncover valuable insights that will benefit players, coaches, sports teams, and fans.

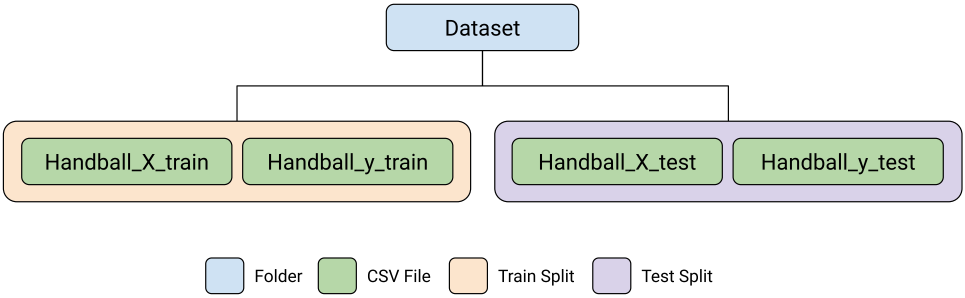

Fig. 1. Folder structure of the provided dataset. The data is partitioned into two folders, one for each split.

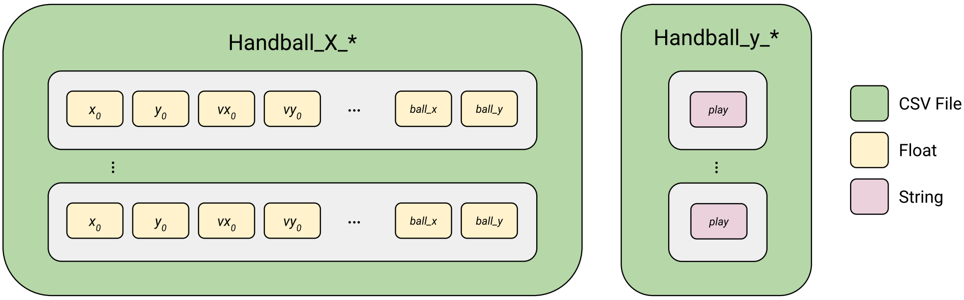

Fig. 2. Depiction of the internal structure of the agent data and its labels. On the left, we have all of the frame data. On the right, we have the corresponding labels for said data. We use the same structure for both splits, train and test, the reason for the wildcard "*" in the filename.

- Other researchers can reuse this dataset to create and test new models. Furthermore, it can assist in creating novel game analysis tools and techniques. It can also be reused to develop automated broadcasting and game summarization tools, which can be especially helpful for smaller sports teams that cannot afford expensive live broadcasting setups or the required staffing.

2. Data Description

This article describes the dataset presented in the linked repository [1]. It consists of multiple *.csv* files that include the game agent data and their respective labels for each game frame. The dataset accounts for the following agents: the 14 players on the court, two referees, and the ball. The structure of the dataset is illustrated in detail in Fig. 1:

Regarding the folder structure, the root directory contains all the *.csv* files. The data are divided into two splits: *train*, which includes ∼70% of the total data and comprises three matches played in the first arena, and *test*, which contains the remaining ∼30% of the data with two games played in the second. There are four files in total, with two per split: "Handball_X_*" which contain the frame data, and "Handball_y_*" which include the corresponding labels. Fig. 2 depicts the file structure for the game agent data and labels for both splits.

For each frame, we provide positions (x, y) and velocities (vx, vy) for 16 game agents (players and referees), ball positions (*ball_x*, *ball_y*), and game situation labels (*play*). If there is missing agent information it is filled with zeros. Positions and velocities are normalized between [0,1] (see Fig. 3). The latter are normalized accounting for a maximum speed of 15 m/s which we consider a reasonable maximum estimate for a human being. The arrangement of agents in the resulting vector is determined by their speed, with players with higher speeds placed towards

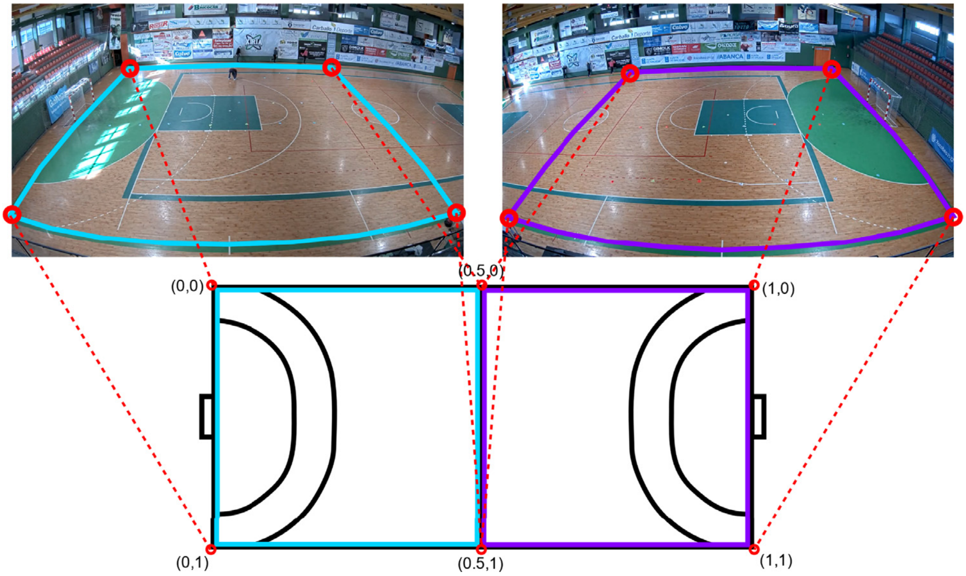

Fig. 3. Representation of the normalized space and its corresponding coordinate limits, and their correspondence with real court limits.

Table 1
List of the possible game situations, their description and number of occurrences in the created dataset.

Situation	Description	Occurrences
Left Attack	Team performs an attack on the left part of the court.	369792
Right Attack	Team performs an attack on the right side of the court.	379910
Left Transition	Team performs a counter-attack from the right side of the court to the left.	94242
Right Transition	Team performs a counter-attack from the left side of the court to the right.	99214
Left Penalty	Team throws a penalty on the left side of the court.	6493
Right Penalty	Team throws a penalty on the right side of the court.	7489
Timeout	Teams are in a timeout.	46264

the beginning of the vector, and slower ones placed towards the end of the vector. The ball is always placed last.

Field and broadcasting experts determined the selection of classes and deemed that the chosen seven were representative enough to describe a handball game from a high-level perspective. Table 1 provides all the relevant information related to the chosen game situations.

For a more comprehensive picture of the classes outlined in Table 1, please consult Fig. 4, it presents a clearer depiction of the seven game situations.

3. Experimental Design, Materials and Methods

3.1. Location

The data was collected by recording videos in two professional handball arenas from Spain:

- Pabellón Vila de Noia - Rúa Vila de Noia, s/n, 15100 Carballo, Spain.
- Pabellón Municipal Vicente Trueba - Av. de la Constitución, 9, 39300 Torrelavega, Cantabria.

The data was collected between February 2019 and September 2020. Video data is not included in the dataset due to commercial and legal reasons (anonymity of the participants). Ap-

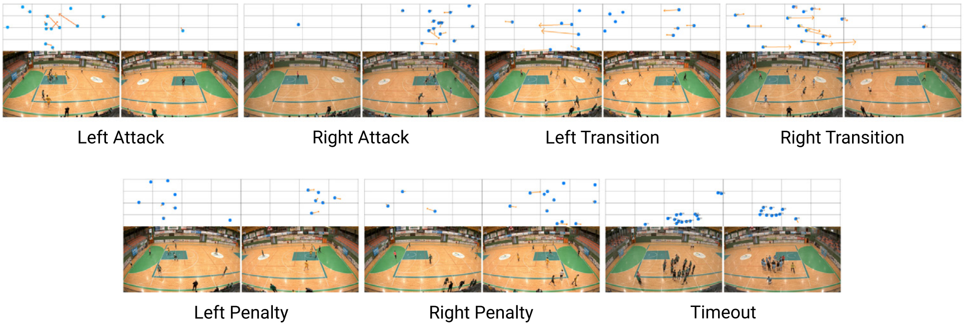

Fig. 4. Example of each game situation and its representation in our normalized space, with positions represented by blue dots, and velocities by orange vectors.

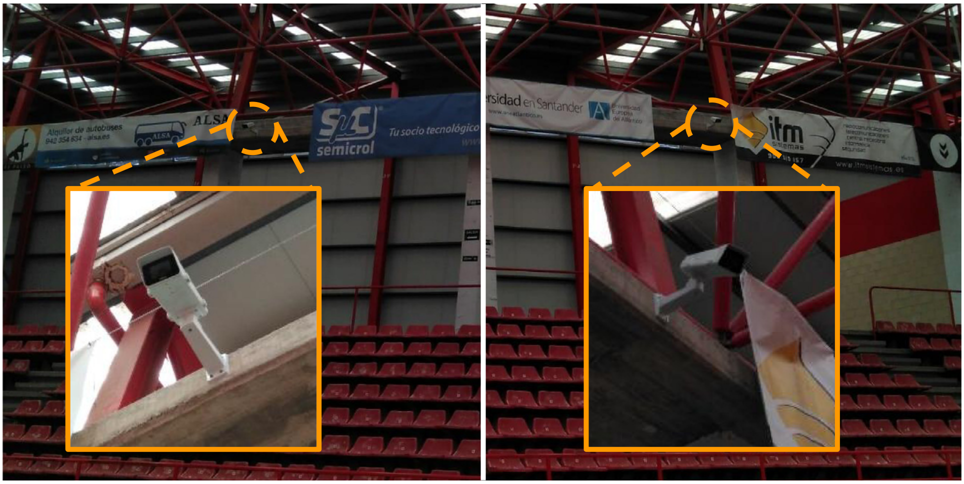

Fig. 5. Image showing the camera installation in the arena “Pabellón Municipal Vicente Trueba”.

proximately 11 hours of playtime (695 min.) were recorded pertaining to five matches. They were played by male professionals from several teams, with different abilities and ages. The participating teams belong to the “Primera División Nacional de Balonmano”, representing the third-tier national category in Spanish male handball. For clarity on the distribution of teams in the captured matches, being the participating teams $T = \{A,B,C,D,E,F,G\}$, the following games were recorded: A vs. C, A vs. D, A vs. E, B vs. F, and B vs. G.

3.2. Data Acquisition

Two AXIS P1468 cameras sporting a resolution of 3840 × 2160 pixels and a 108° field of view were installed in the “Pabellón Vila de Noia”. In addition, two AXIS M1125 with a 1920 × 1080 resolution and a 91° field of view were installed in the “Pabellón Municipal Vicente Trueba” (refer to Fig. 5 for a photo of the installation). They were static and covered both halves of the court (refer to Fig. 6 for a schematic of the camera configuration). Frames were synchronized using Network Time Protocol (NTP) to ensure temporal coherence between both cameras. The video data was streamed to our servers using Real-Time Transport Protocol (RTP), a network protocol that delivers audio and video over IP networks.

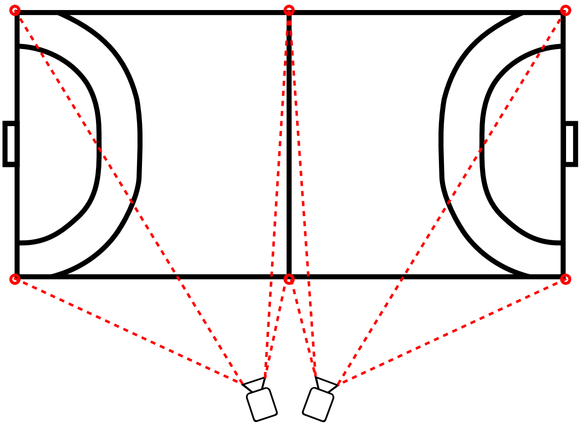

Fig. 6. Diagram depicting the chosen camera setup.

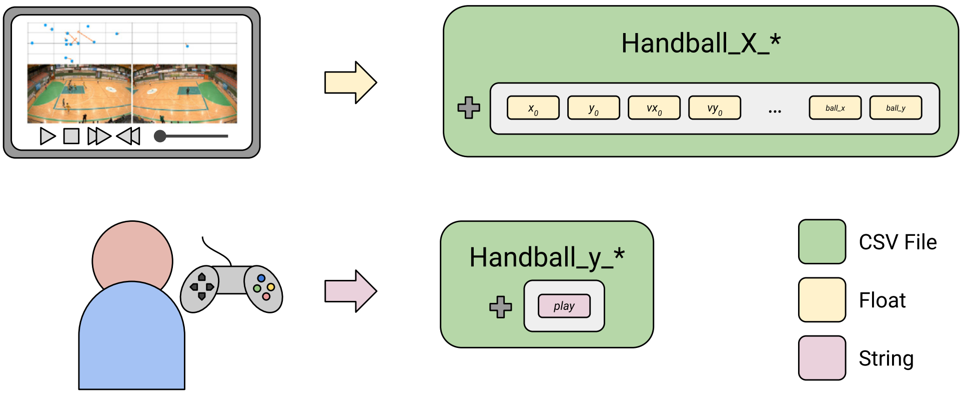

Fig. 7. Flow chart of the data annotation pipeline. The annotator selects the type of play that is associated to a certain frame, the system obtains the associated frame data, and stores both in their corresponding data files.

3.3. Data Labeling

Regarding data labeling, we developed an in-house labeling tool that allowed the experts to review the video footage (play, pause, rewind, and change speed). The tool also allowed to set each of the frames' game situations using seven predefined buttons, that when pressed, switched to a particular game situation. The resulting information was saved in a *.csv* file. The tool was implemented using *Python*, *ffmpeg*, and *PyGame* (see Fig. 7 for a graphical description of the system). The data was evenly distributed among the annotators. In more intricate scenarios where uncertainties arose, they jointly decided what the final output was. To improve accuracy and avoid fatigue, the annotators scheduled breaks of at least 15 minutes after every hour-long annotation session.

3.4. Data Analysis and Filtering

To obtain the final agent dynamics, including positions and velocities, we carried out a sequence of steps on our cloud servers (G4 AWS instances), leveraging the capabilities of GPUs. These steps, depicted in Fig. 8, included:

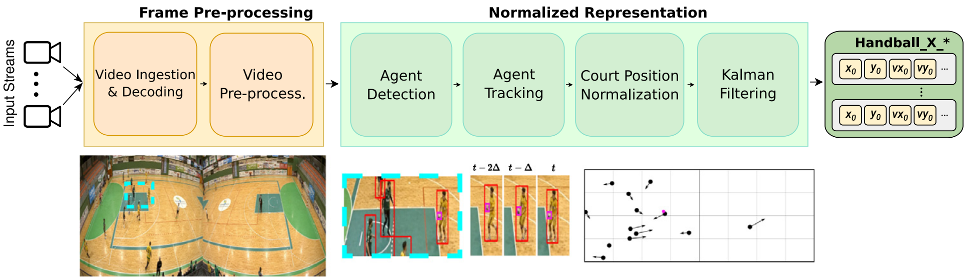

Fig. 8. Diagram describing the data analysis and filtering pipeline. Frames are decoded and pre-processed, players and ball are detected and tracked, their positions are normalized, processed with a Kalman filter and finally stored in a .csv file.

- Raw frame decoding using NVDEC to leverage *h.264* hardware decoding for maximum performance.
- Pre-processing with NPP leveraging the GPU to perform pixel-format conversions (NV12 to RGB), cropping (area of interest), re-sizing (area of interest to 1664 × 832), and color-remapping ([0,255] to [0,1]).
- Utilizing a YOLOv4 [2] object detector to obtain the positions of players, referee, and ball. The employed object detector achieved a mean Average Precision (mAP) of approximately 94% for players and 85% for the ball. Players are also tracked across multiple frames using a custom tracking algorithm. This algorithm combines two widely recognized metrics, Intersection over Union (IoU) and Euclidean distance, as detailed in the accompanying paper [3]. Although the tracking algorithm is robust enough for our purpose (estimating player speeds in real-time), it may not be the most suitable option for tracking players throughout the entire match.
- Normalizing the coordinates using a "bird's view" perspective transformation [4] to achieve camera setup independence. This transformation addresses perspective distortion but does not account for lens distortion.
- Employing a Kalman filter [5] for further processing, resulting in more reliable positions and velocities. We carefully evaluated the results and found that the player position yielded by the object detector was robust enough to track players and estimate player speeds. However, we noticed that the detections for the ball were not consistent enough to obtain precise speeds due to missing trajectory frames.
- Lastly, saving the resulting information to the corresponding .csv files.

Limitations

It should be noted that due to the nature of handball games, there is a clear class imbalance. As shown in Table 1, left and right attacks (∼600K occurrences) are much more common than left and right penalties (∼14K occurrences).

Ethic Statement

We collected this dataset following ethical principles and guidelines and with the previous consent of the players, coaches, and referees participating in the matches. We excluded video footage to protect the privacy of the individuals involved, and avoid including any personally identifiable information.

In light of these considerations, the necessity for formal ethics approval from an Institutional Review Board (IRB) or local ethics committee was not deemed necessary. The decision to forgo formal ethics approval was underpinned by the fact that the dataset collection presented no risk to participants and the absence of sensitive or potentially harmful content in the dataset.

Data Availability

PlayNet: Real-time Handball Play Classification with Kalman Embeddings and Neural Networks Dataset (Original data) (Zenodo)

CRediT Author Statement

Omar A. Mures: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization; **Javier Taibo:** Conceptualization, Methodology, Validation, Investigation, Writing – review & editing, Supervision; **Emilio J. Padrón:** Conceptualization, Methodology, Validation, Investigation, Writing – review & editing, Supervision, Project administration; **Jose A. Iglesias-Guitian:** Conceptualization, Methodology, Validation, Investigation, Writing – review & editing, Supervision.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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