Volleyball Action Modelling for Behaviour Analysis and Interactive Multi-modal Feedback

Abstract

The goal of this project is to create new forms of volleyball training using multi-modal sensor data and interactive displays to provide analysis and feedback in an innovative manner. The project will use X-Sense MTw Avinda sensors strapped on the wrists and head of volleyball players to capture motion data and use Machine Learning techniques to model their actions (such as under hand serve, overhead pass, serve, forearm pass, one hand pass mash and under hand pass) and posture balance while performing actions (to avoid injuries) during matches and training sessions. The trained model will be used in supplementing video recordings by providing tailored and interactive multi-modal feedback to coaches and players by utilizing an html5/JavaScript application.

Lead Organizers:

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1. Introduction and Background Information

Top performance in sports depends on training programs designed by team staff, with a regime of physical, technical, tactical and perceptual-cognitive exercises. Depending on how athletes perform, exercises are adapted, or the program may be redesigned. State of the art data science methods have led to ground breaking changes. Data is collected from sources such as tracking position and motion of athletes in basketball (Thomas, Gade, Moeslund, Carr, & Hilton, 2017) and baseball and football match statistics (Stensland et al., 2014).

Furthermore, new hardware platforms appear, such as LED displays integrated into a sports court (Kajastila, 2015) or custom tangible sports interfaces (Ludvigsen, Fogtmann, & Grønbæk, 2010). These offer possibilities for hybrid training with a mix of technological and non-technological elements (Kajastila, 2015). This has led to novel kinds of exercises (Jensen, Rasmussen, Mueller, & Grønbæk, 2015a, 2015b; Ludvigsen et al., 2010), including real-time feedback, that can be tailored to the specifics of athletes in a highly controlled way. Data science tools can then be used to precipitate tailored modifications to (the parameters of) such training.

These developments are not limited to elite sport. Interaction technologies are also used for youth sports (e.g., the widely used player development system of Dotcomsport.nl¹), and school sports and Physical Education (Koekoek, van der Mars, van der Kamp, Walinga, & van Hilvoorde, 2018).

This project aims to extend the state of the art by combining sensor data, machine learning and interactive video to create new form of volleyball training and analysis. It will do so by automatically identifying volleyball player actions and tagging to enahnce the video based feedback.

2. Objectives

Following are the objectives of the project

- 1) Evaluate the potential of using sensor data from IMUs (3D acceleration, 3D angular velocity, 3D magneto meter and air pressure) in automatically identifying basic volleyball actions such as:
 - a. under hand serve,
 - b. overhead pass,
 - c. serve,
 - d. forearm pass,
 - e. one hand pass,
 - f. smash,
 - g. underhand pass
- 2) Body Posture detection: The hand, finger and knee injuries are very common in Volleyball (Solgard et al., 1995), which could happen by following an action with a wrong posture such as fingers are not closed properly while passing the volleyball or use of interlocking fingers. However, identifying the posture which may lead to injury while performing an action could help players in avoiding that posture.
- 3) Use Machine Learning techniques to identify:
 - a. Individual player actions
 - b. Coordinated team actions i.e. events like rallies and points.

¹ <u>https://dotcomsport.nl/nl/spelervolgsysteem-dotcomclub/</u> last verified: February 2019.

- 4) Supplement the video recording by tagging the identified action and events.
- 5) Allow coaches and players to view tagged video footage to easily search for the information or event of interest e.g.:
 - a. All the serves by a particular players
 - b. All the rallies in which the team gain points.
 - c. Players individual actions in relation to each other etc.

3. Research Questions

Following are the research questions assessed by this project.

- 1) To what extent can sensor data be used to identify basic volleyball actions of individual players?
- 2) To what extent can sensor data be used to identify body postures which could lead to an injury?
- 3) To what extent can the volleyball action identified in question 1 be used to identify coordinated action by volleyball team?
- 4) How can visual feedback (video recording supplemented by multimodal sensor data) be used to add value to training sessions?

4. Requirements

- X-Sense MTw Avinda kit (Provided by BSS).
- Access to volleyball court.
- Volleyball players to wear the sensors and train or play matches (if not possible to collect data in Ankara, subset of data collected by BSS and partners may be available to be used).

5. Technical Setup

5.1 Data Recording

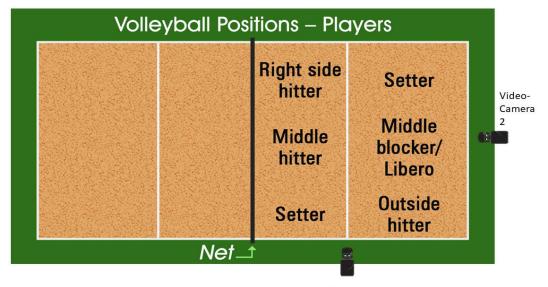
- 1) Each player wears either 3 IMUs (see Figure 1) on the head and wrists or 1 IMU on the dominant wrist.
- 2) Two video cameras on the side of team wearing the IMUs (see Figure 2).

5.2 Data Annotation and Model Training

- 1) Elan software for manual annotation.
- 2) Matlab and/or Phython for model training.



Figure 1: Player wearing 3 IMUs (Head and wrists)



Video-Camera 1



5.3 System Components

Figure 3 shows the components of the system. Features are extracted from sensor data to train the Machine Learning models. Time aligned video footage and other data is stored in the data repository. Coaches or players can use the front-end application to explore the information of interest (see Figure 4).

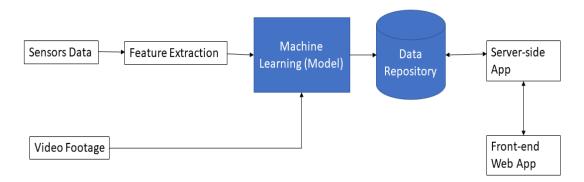
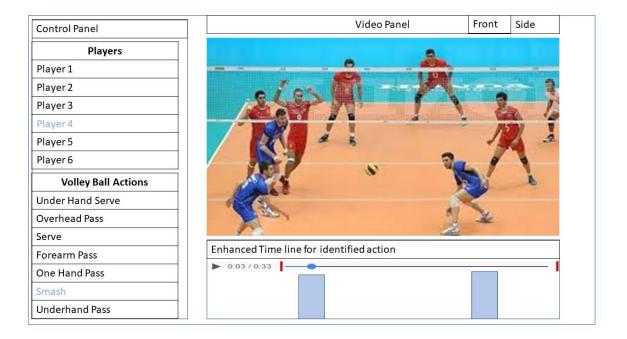


Figure 3: System Component Diagram.

Figure 4 shows a mock-up design of the front end app. Users can filter the information per player or action and the enhanced timeline would show the points where the searched actions occur. Users can choose between front view and side view. The interface can be enhanced to display additional information for coaches and players.





6. Work Packages

6.1 WP1: Data Collection, Synchronization and Annotation.

- In this work data will be collected by using sensors and video cameras during training sessions and/or matches (see section 5.1)
- Collected data will be annotated using the Elan annotation tool (see Figure 5) for volleyball actions and body posture.

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	21 Forearm Pass			00:01:57:555 00:01:58.945 00:00:01:380
	22 Smash			00:02:09.860 00:02:11.440 00:00:01.580
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Figure 5: Annotation with Elan annotation tool.

6.2 WP2: Model Training

In the work package the data collected from WP1 will be used to training the models for volleyball action, body posture and event identification.

6.3 WP3: Application Development

In this work package the software component of the systems will be developed (see 5.3).

6.4 WP4: Integration and Testing

This work package the system will be tested with real users.

7. Deliverable

7.1 D1: Annotation and synchronization of Data (week 1)

In the first week some members of the project team would be working on data collection and annotation i.e. they would be working on WP1.

7.2 D2: Trained Models (week 2)

In the second week some members of the team would be working on training the models, i.e. WP2.

7.3 D3: Initial App prototype (Week 1 & 2).

For the first two weeks some member of the team will be working on the application development portion of the project i.e. WP3 (see section 5.3).

7.4 D4: Functional prototype for testing (Week 3)

In the 3rd week, the parallel development of the applications and trained models will be integrated to get a functional prototype.

7.5 D5: Field Tested Prototype (Week 4)

In the final week the final prototype will be tested and refined (WP4).

8. Benefits of the Research

The multidisciplinary approach of the project will be beneficial in many regards for example:

8.1 Data science

Development of novel tools and algorithms for understanding sensor data from volleyball activities.

8.2 Interaction Research

User experience design, (embodied) game design.

8.3 Sports Training and Pedagogy

Sports training, sports education, physical education, and the teaching of future trainers.

9. Why Join the Team

Join the team if you are interested in:

- Multidisciplinary Research
- Multimodal Signal Processing
- Working with sensors like IMUs
- Machine Learning
- Software Development
- Smart Sports
- Sports Training and Pedagogy
- Play Volleyball

10. Team Profile

10.1 Fahim A. Salim

Fahim A. Salim is a Post-Doc researcher at Biomedical Signals and Systems Group, University of Twente. He is currently working on the Smart Sports Exercises project which utilizes IMU sensors and pressure sensitive in floor displays to offer tailored and interactive exercise activities in the context of volleyball training and analysis. Fahim's research interest is to combine Multimodal Signal Processing and Human Media Interaction approaches in multidisciplinary applications. His PhD research at the ADAPT centre Trinity College Dublin was about automatically transforming video content by extracting multimodal features (Visual, Audio/Paralinguistic and Linguistics) and representing them to users as an adaptive interactive multimedia document based on the context. Before becoming a researcher, he was a software engineer at the Italian subsidiary of PIKSEL Inc. where he worked on several projects related to video content management for clients which included major media conglomerates from different countries.

10.2 Bert-Jan van Beijnum

Dr. ir. B.J.F. van Beijnum is associate professor at the faculty of Electrical Engineering, Mathematics and Computer Science. His research addresses smart technologies for remote monitoring, analysis and feedback technologies for patients with chronic conditions, support of lifestyle changes and sports. He is involved in projects on methods and technologies for monitoring stroke patients in daily life, development of rehabilitation devices for stroke, monitoring coaching and behavioural modelling of type 2 diabetes patients, qualitative assessment of rehabilitation after hip fractures, minimal sensing for motion capturing and running, modelling athlete behaviour for smart sports exercises.

Webpage: https://people.utwente.nl/b.j.f.vanbeijnum

10.3 Fasih Haider

Dr Fasih Haider is a Research Fellow in the Usher Institute of Population Health Sciences and Informatics, Edinburgh Medical School, at the University of Edinburgh, UK. His areas of interest are Social Signal Processing and Artificial Intelligence. Before joining Usher Institute, he worked as a Research Engineer at ADAPT centre where he worked on methods of Social Signal Processing for video intelligence. He obtained a PhD in Computer Science defending the thesis "Improving Social Intelligence of Machines in the Context of Public Speaking Situations" from Trinity College Dublin, Ireland. Fasih is the author of more than 25 publications and has presented his work in numerous international conferences. Currently, he is working on the EU-H2020 project SAAM and researching on the social signal processing and machine learning methods for monitoring the cognitive health of humans.

Webpage: <u>https://www.research.ed.ac.uk/portal/en/persons/fasih-haider(77c8d280-a1af-4b77-aeca-</u><u>9736110d0d11).html</u>

10.4 Saturnino Luz

Saturnino Luz is a Reader and Chancellor's Fellow ate the University of Edinburgh. He conducts research in medical informatics, employing machine learning, natural language processing, and signal processing methods to the study of behaviour and communication in healthcare contexts. His primary interest is in the use of computational methods in the study of behavioural changes caused by neurodegenerative diseases, with focus on vocalisation and linguistic behaviour. He has also employed these methods in the investigation of interaction in multidisciplinary medical team meetings, doctor-patient consultations, telemedicine and health promotion. His research interests also include visualisation of and inference in high dimensional data sets, and graphical models. Dr Luz is the Edinburgh University lead for the H2020 SAAM project, aimed at supporting active ageing through multimodal coaching.

Webpage: <u>https://www.research.ed.ac.uk/portal/en/persons/saturnino-luz-filho(492fc0f5-30f4-42c0-b53f-0a2098a74cbc).html</u>

10.5 Kübra Cengiz

Kübra Cengiz is a PhD student and a research assistant at Faculty of Computer and Informatics Engineering, Istanbul Technical University, Turkey. Her areas of interest are Computer Vision, Medical Image Processing and Machine Learning.

11. Prospective Participants

Required

2 Developers with working knowledge of HTML5/Java script and a server side technology.

2 to 3 people with working knowledge or willingness to learn data collection and annotation.

1 to 2 researchers with working knowledge of machine learning techniques.

1 to 2 researchers with the working knowledge of time series data analysis and signal processing methods.

Desired

Volleyball players willing to wear IMUs and play while data is recorded. Researchers interested in Sports Training and Pedagogy.

12. References

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