Explainable Machine Learning with Shapelets for Swimming Proficiency Analysis

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Summary

This study leveraged computer vision and machine learning to identify key motion patterns defining swimming technique levels. A customized YOLOv8 human pose estimation model enabled the calculation of joint angle trajectories, from which Shapelets were derived, to classify swimming level with 90% accuracy. The key findings offer objective insights into swimming performance and highlight the importance of making efficient movements in the catch and push phases and maintaining a bent elbow at the end of the push phase.

Introduction

Mastering proper technique is essential for excellence in swimming. While freestyle swimming guidelines exist, coaches often rely on subjective evaluations without explicitly defining their parameters. This study aimed to identify and parameterize the factors that determine swimming level by using Shapelets to identify key patterns in motion trajectories. Shapelets are representative subsequences within time series data that can provide interpretable and actionable insights into factors that determine proficiency levels.

Methods

An experienced swimming coach ranked the freestyle swimming technique observed in 49 sagittal view videos of swimmers, who ranged from beginners to Olympic medalists (15–58 years), on a continuous scale from 0 to 4. Swimmers scoring 0 to 2 were labeled as developing swimmers (26 videos), while those with a score of 3 or 4 were considered elite swimmers (23 videos). A total of 39 videos were used for training, and 10 videos were used for testing.

All videos were analyzed with our single-camera markerless swimming biomechanics system. The system employed a customized YOLOv8 deep learning–based computer vision model for human pose estimation to predict joint locations across frames. Next, joint and segment angle time series were calculated and segmented into swimming cycles, interpolated to 100 timestamps to normalize cycles as 100% of the motion, and averaged per swimmer to generate a representative cycle.

Learning Shapelets models (by tslearn) were trained for each joint and segment angle time series to identify those Shapelets that distinguish between the elite and developing levels of swimming technique. Twelve Shapelets that were consistent in their timing within the swimming cycle were extracted to represent key motion events. The minimal squared Euclidean distance to each Shapelet was calculated and used as features in a random forest to classify swimmers' proficiency levels. Feature importance analysis was used to assess the contribution of each Shapelet to classification performance.

Results and Discussion

Most Learning Shapelets classifiers achieved over 80% accuracy and F1 scores above 85%, with the random forest classifier achieving 90% accuracy and an F1 score of 92.3%. Feature importance analysis identified three main Shapelets—two from shoulder angles and one from elbow angles—with each spanning 10 timestamps.

The first shoulder Shapelet depicted a moderate angle decrease during the catch phase (~160° to ~153°) at around 30% of the cycle. Elite swimmers exhibited a steeper decrease compared to developing swimmers. The second shoulder Shapelet showed a moderate angle decrease from the pull into the mid-push phase (~115° to ~47°) at around 50% of the cycle. Elite swimmers exhibited greater angular velocity and larger changes (Figure 1A). The elbow Shapelet revealed that elite swimmers maintained an elbow angle of ~130° before the recovery phase, while some of the developing swimmers displayed larger angles (Figure 1B).

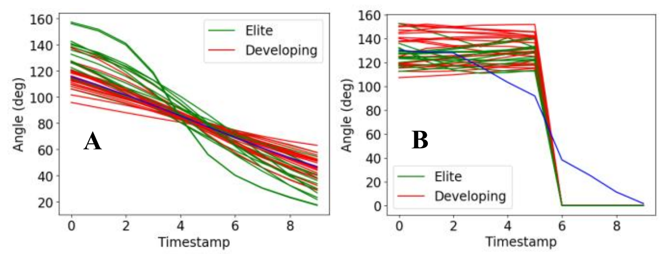

Figure 1: A) The second shoulder and B) elbow Shapelets, with learned Shapelets shown in blue. Note: In B, as the hand exits the water, the angle is set to 0.

Conclusions

Using data from our swimming pose estimation system as input for a random forest classifier based on Shapelets, we uncovered key biomechanical patterns that differentiate swimming proficiency. These patterns provide explainable and actionable insights for technique refinement and a data-driven framework for enhancing swimming performance.

Acknowledgments

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