

Swimming Style Recognition with Convolutional Neural Network with Single IMU

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Abstract

The study focuses on swimming style recognition using a Convolutional Neural Network (CNN) and a single inertial measurement unit (IMU) located on the wrist, mimicking the setup of a typical smartwatch. Traditional methods often employ multiple sensors or sensors placed in impractical locations, limiting everyday usability for swimmers. This research utilizes data collected from 40 swimmers, integrating 53,732 input windows from sessions in a 50-meter pool, where swimmers wore a smartwatch on their wrist. The CNN model was modified to enhance pattern recognition capabilities across swimming styles: Butterfly, Backstroke, Breaststroke, Freestyle, and Transitions. Enhanced data processing techniques, including normalization and augmentation (time-scaling, noise addition, reversing, and rotation), were applied to simulate real-world variances. The model was evaluated using a Leave-One-Subject-Out (LOSO) cross-validation method, demonstrating high precision and minimal misclassification, signifying a robust model capable of accurately detecting and classifying swimming strokes with potential for real-time application in sports and health monitoring. This approach offers a significant improvement over previous systems by reducing the sensor complexity and focusing on individual movement patterns, potentially increasing the accessibility and precision of swimming activity recognition.

Keywords

Convolutional Neural Network (CNN); inertial measurement unit (IMU); swimming style recognition.

1. INTRODUCTION AND RELATED WORK

Smartwatches have become increasingly popular, with many people wearing them daily, particularly for sports activity monitoring. For swimmers, these devices typically offer features like lap counting, stroke detection, and real-time performance tracking. However, most current studies on swimming style detection rely on multiple sensors [1,3,7,10] or sensors placed in less practical locations, such as the lumbar region or sacrum. [1,2,3,7,10] Bächlin et al. [1] collects motion data with 3-axis accelerometers placed on the upper and lower back and wrists to develop a wearable computing system to support swimmers in improving performance and technique by monitoring and providing feedback. Delhaye et al. [2] uses a single Inertial Measurement Unit (IMU) attached to the sacrum to create a deep learning model to analyze swimming activities and classify eight swimming classes. Fantozzi et al. [3] also uses Inertial sensors on the head, wrists, and ankles to develop a tool for stroke-by-stroke evaluation of stroking, kicking, and breathing in front-crawl swimming. Mooney et al. [7] uses IMU sensors placed on wrist, lower back, and chest to capture different aspects of swimming motion for their stroke recognition algorithm. Wang et al. [10] utilizes a sensor node with MEMS sensors (3-axis gyroscope, accelerometer, magnetometer) placed on the lumbar to develop a system (SwimSense) for analyzing swimming motion and recognizing posture using wearable inertial

sensors. To improve accessibility and usability, research should focus on methods that utilize only the internal inertial measurement unit (IMU) located on the wrist, simulating the conditions of standard smartwatches.

Many current studies utilizing wrist IMU sensors rely on generalized models that combine data from various users into a single system. While these models have successfully been developed to recognize swimming styles and count laps using deep learning algorithms, they often overlook individual differences in swimming techniques. As a result, generalized models trained on diverse datasets may lack the precision needed to capture the unique nuances of each swimmer's movements. A more individualized approach, where the model is tailored to the specific patterns of a swimmer's technique, could improve accuracy by focusing on the personal characteristics of their movements [5,6,8,9].

In this particular instance, a dataset will be run as individualized models and compared to a more generalized model, potentially increasing accuracy of stroke recognition. The data, methodology and code used is from Brunner et al. and their paper Deep learning and model personalization in sensor-based human activity recognition [11] from their github source.

2. DATA COLLECTION

Data was collected from 40 swimmers of diverse backgrounds, totaling 17 hours of sensor data. The participants ranged from competitive swimmers to recreational swimmers, aged 25 to 75 years from a masters swim club. The data was captured during regular training sessions in a 50-meter indoor pool, where at least ten swimmers shared a lane, simulating real-world conditions. The swimmers wore a waterproof smartwatch ("Nixon The Mission") on their preferred wrist during their usual training routines, and data from sensors such as accelerometer, gyroscope, magnetometer, barometer, and ambient light sensor was recorded. The data collection app was designed with a simple user interface to minimize errors and frustration.

The dataset contains records for four main swimming styles (front crawl, breaststroke, backstroke, butterfly) and transitions (turns and rests), which were manually labeled. The data was segmented into windows with a 5-second overlap, and each window was labeled based on the predominant activity during the window. The final dataset comprised 53,732 input windows used for training and testing.

The sensor data was pre-processed by resampling all channels to a uniform sampling frequency of 30 Hz using cubic spline interpolation, creating 6-second windows (180 samples each). Each signal channel was normalized to ensure zero mean and unit variance, and data windows labeled as 'unknown' were excluded, resulting in 53,732 windows for model training. To enhance the model's generalization, four data augmentation techniques were employed: time-scaling, which simulated variations in swimmer speed by adjusting the time dimension; noise addition, which involved adding Gaussian noise to improve robustness against random fluctuations; reversing, which replicated how signals might differ if the watch were worn on the opposite wrist; and rotation, which applied random rotations to mimic different watch orientations on the wrist.

3. METHODOLOGY

In this study, a modified Convolutional Neural Network (CNN) architecture was used for swimming style classification. Compared with the original paper, the modified neural network consists of six convolutional layers, each utilizing 3x3 filters to capture more complex spatiotemporal patterns. Max-pooling operations were replaced with adaptive pooling layers to allow the network to dynamically adjust pooling operations based on data distributions. After feature extraction, the resulting information was passed through a fully connected layer, and

the final classification output was generated using a softmax activation function to predict the five swimming styles: Butterfly, Backstroke, Breaststroke, Freestyle, Transition. To prevent overfitting and improve the model's generalization, batch normalization was employed after each convolutional layer, stabilizing the training process. Furthermore, the Ranger optimizer, which integrates the advantages of RAdam and Lookahead, was utilized for faster and smoother convergence compared to ADAM. To handle class imbalance, focal loss was applied, placing greater emphasis on difficult-to-classify examples, which contributed to improved performance across underrepresented classes. Model evaluation was performed using Leave-One-Subject-Out (LOSO) cross-validation, identical to the paper, where data from each participant was tested against a model trained on data from all others, providing a strong measure of generalizability across users.

4. RESULTS

Table 1. Confusion matrix compared with the original paper(original results are in brackets)

True Class	Predicted Class				
	Butterfly	Backstroke	Breaststroke	Freestyle	Transition
Butterfly	97.4% (96.5%)	0(0)	0 (0)	2.3% (3.4%)	0.3% (0.1%)
Backstroke	0 (0)	97.9% (98.2%)	0 (0)	0.4% (0.4%)	1.6% (1.2%)
Breaststroke	0 (0)	0.7% (1.7%)	97.6% (94.9%)	0.8% (1.8%)	0.9% (1.7%)
Freestyle	0.2% (0.5%)	0.5% (0.1%)	0 (0)	98.4% (98.5%)	0.7% (0.8%)
Transition	0.1% (0)	0.3% (0.3%)	0.2% (0.2%)	0.7% (0.7%)	98.8% (98.7%)

Leave-One-Subject-Out (LOSO) evaluation was used to assess the model's performance. In this approach, data from one participant serves as the test set, while data from all other participants is used for training. The network was trained for a fixed number of epochs, with performance continuously monitored on the validation set. The model achieving the highest normalized accuracy on the validation set was then applied to the left-out participant's data for final evaluation.

The confusion matrix provided in Table 1 demonstrates the effectiveness of the proposed model in accurately classifying various swimming styles and transitions. Overall, the model exhibits high precision and a minimal misclassification rate across all classes, highlighting its ability to accurately distinguish between different swimming strokes. A detailed analysis of each class is outlined below:

For the Butterfly class, the model achieved an accuracy of 97.4%, with a minor misclassification rate of 2.3% for Freestyle and 0.3% for Transition. This indicates that the model is proficient in identifying Butterfly strokes, with only minimal confusion between Butterfly and other styles. The Backstroke class was classified with an accuracy of 97.9%, with

small errors occurring in the Freestyle (0.4%) and Transition (1.6%) categories. These errors suggest that while the model performs well overall, some overlap in sensor data patterns, particularly during transitions, still exists. The Breaststroke class was recognized with a precision of 97.6%, showing slight confusion with Backstroke (0.7%) and Freestyle (0.8%). This minor overlap may indicate similarities in the data captured from the sensor for these strokes, though the model performs comparably well in distinguishing Breaststroke from other classes. The Freestyle class was predicted with high accuracy (98.4%), with negligible misclassifications of 0.2% for Butterfly and 0.5% for Backstroke, reflecting the model's strong ability to detect Freestyle strokes. The Transition class demonstrated excellent performance, achieving an accuracy of 98.8%. Misclassifications in this category were minimal (0.2%-0.7%), showing that the model is particularly adept at recognizing periods of transition between strokes. This improvement in detecting transitions is especially notable, given that such periods are often challenging to classify due to variability in movement patterns.

Compared to the original model, the proposed model demonstrates similar or improved performance in most areas. The Butterfly class shows a notable improvement (97.4% vs. 96.5%), with reduced confusion with Freestyle (2.3% vs. 3.4%). Backstroke classification remains consistent (97.9% vs. 98.2%), though there is slightly higher confusion with Transition (1.6% vs. 1.2%). Breaststroke accuracy improved (97.6% vs. 94.9%) with fewer misclassifications into Backstroke and Freestyle, indicating that the proposed model captures subtle differences better. Freestyle remains highly accurate (98.4% vs. 98.5%) with little confusion between strokes. Lastly, Transition classification shows a slight improvement (98.8% vs. 98.7%), reflecting enhanced feature extraction techniques or regularization strategies in the new model.

5. CONCLUSION

In all, the proposed model shows strong classification accuracy across all swimming strokes, with notable improvements in recognizing the Butterfly and Transition classes compared to the original model. While slight misclassifications persist, particularly between strokes with similar movement patterns, the overall performance of the model is highly reliable. The enhancements made in feature extraction and classification strategies contribute to the model's robustness, making it an effective tool for swimming style recognition. Furthermore, the ability of the model to generalize across different classes and reduce errors highlights its potential for application in realistic swimming environments.

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