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Movement Prediction in Rowing using a Dynamic Time Warping based Stroke Detection

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***Abstract*—In professional rowing competitions, sensor data is transmitted from an on-board sensor unit on the boat to an external computer system. This system calculates the current position of each boat in real-time. However, incomplete localizations occur as a result of radio transmission outages. This paper introduces an algorithm to overcome transmission outages by predicting the rowing movement.**

The prediction algorithm is based on accelerometer and GPS data that is provided by the on-board unit before an outage occurs. It uses Subsequence Dynamic Time Warping (subDTW) to detect the rowing strokes in the acceleration signal. Knowing the previous strokes, the system predicts the upcoming strokes, as the rowing motion follows a periodic pattern. Thereby, the GPS measured velocity can be extrapolated and the position is predicted. A further outcome of the subDTW stroke detection is an accurate determination of the rowing stroke rate.

In our experiment, we evaluate the rowing stroke detection and stroke rate determination based on subDTW as well as the prediction algorithm for simulated outages of professional race data. It shows a subDTW stroke signal detection of 100% after the start phase of the race. The prediction in case of a sensor outage of 5 seconds leads to a correlation between the predicted velocity and the actual velocity of 0.96 and a resulting position error (RMSE) of 0.3 m.

I. Introduction

A. Motivation

Accurate localization of rowing boats in international competitions is a key element for television broadcasting. The television audience often has a hard time following the competition development, because the camera perspective commonly does not allow straightforward deduction of race standings. Therefore, the broadcasting industry has a high demand for real-time localization systems.

In principle, localization is enabled by Global Positioning System (GPS) and Inertial Measurement Unit (IMU) on-board sensor data, which is transmitted to a land-based control station. This station calculates the current position of each boat. However, transmission outages occur that result in incomplete localization of the boats. This paper introduces an algorithm to bridge transmission outages by accurately predicting boat positions in the outage time gaps.

The algorithm uses a Subsequence Dynamic Time Warping (subDTW) based stroke detection. Based on a predefined template of a rowing stroke, the algorithm segments the acceleration signal of the on-board sensor unit. The acceleration signal is synchronized with the velocity signal of the GPS and the start and end times of the detected strokes can be applied directly to the velocity signal. The prediction algorithm extrapolates the velocity during transmission outages taking advantage of the periodic rowing motion.

B. Related work

An extensive analysis of the rowing motion is given by Kleshnev [1]. The cyclic character of the motion is explained by analyzing the acceleration signal and segmenting it into single stroke phases. King et al. [2] describe the general use of inertial sensors in rowing and identify poor rowing techniques with their Body Sensor Network.

The focus of this work is on the processing of the acceleration and the GPS data. By implementing the subDTW based stroke detection algorithm two contributions were made: a stroke rate detection using IMU acceleration data and the actual prediction algorithm to overcome outages.

Different approaches for the stroke rate detection were introduced in previous work. Tessendorf et al. [3] used two IMUs. A first one was attached to the boat and a second one was attached to the oar in order to the detect its orientation at all times. Counting the horizontal oar angle pose, rowing strokes could be recognized. A commercial alternative was presented by the StrokeCoach of Nielsen-Kellermann [4]. It calculated the stroke rate based on the movement of the seat.

To our knowledge, the subDTW based stroke rate calculation, as proposed in this work, has not been mentioned in related literature before. However, Dynamic Time Warping (DTW) and Subsequence Dynamic Time Wapring is widely used in the field of Pattern Recognition. DTW is a nonlinear mapping algorithm that calculates the distance function between two signals. Berndt et al. [5] described the general use of DTW. By the extended version of subDTW, as proposed by Müller in [6], patterns can continuously be detected in an ongoing signal. Applications can be found in various fields as for example in the subDTW based step detection of Barth et al. [7]. Here, a gyroscope was attached to a shoe and the DTW algorithm analyzed the walking motion by detecting the steps. Horst [8] introduces the Fast Incremental Dynamic Time Warping (FIDTW). The computation time optimized DTW approach executed spatial and temporal matching of sensor data in sports applications.

In comparison to Tessendorf et al. [3], the stroke detection of this work relies on only one sensor unit that theoretically can be installed at any stable location of the boat as the acceleration of the boat as a rigid body is measured and processed. The implemented subDTW algorithm analyzes the acceleration signal instead of the gyroscope. Besides the stroke detection function, the implemented algorithm of this work provides a prediction of the future movement of the rowing boat.

II. Methods

A. Data collection

The necessary sensor hardware was integrated in an on-board module that was mounted to the bow of the boat. It included a 3D-acceleration sensor (Analog Devices ADXL330, range: ± 3 g, resolution: 10 bit) with a 50 Hz sampling rate and a low-cost GPS unit (u-blox 6, set to 'automotive' profile) with 5 Hz sampling rate that provided the GPS determined velocity and position. The data collection was performed at the U23 World Championship in Linz. The focus was on the boat class eight coxed (data class 1, eight rowers per boat plus coxswain, one oar) and single scull (data class 2, one rower per boat, two oars). For both classes data was acquired: race data of heats, repechages and (semi-) finals for data class 1 and final races for data class 2. For each race type two boats were analyzed, one of a men and one of a women race. An overview of the data classes is provided in table I. One data set represents one race.

The training data was exclusively taken from data class 1 (eight data sets) and considered all race types and both genders. The evaluation was based on four data sets: the final races of class 1 and class 2 (each with one men, one women race).

The acceleration signals of both classes were analyzed manually and all strokes were labeled for the stroke detection evaluation. The evaluation of the position prediction algorithm was based on a real time kinematic GPS system (RTK). The RTK system processed the on-board GPS data in combination with a land-based GPS antenna (Trimble LV59 GNSS Antenna and uBlox EvalKit). It accurately determined the ground truth position data with an inaccuracy of less than 10cm [9], [10]. For an accurate evaluation, all GPS data, not only the reference position, was adapted and improved by the RTK system. However, the prediction application itself does not rely on highly-accurate position data and works with standard GPS without the use of RTK.

TABLE I. Overview of used race data sets

	data class 1	data class 2
race types	eight coxed (men/women)	single scull (men/women)
data collection	8 data sets ∼234 strokes each	2 data sets ∼237 strokes each

B. IMU based stroke detection and stroke rate calculation

1) Template creation: The training data was used to create the template of a rowing stroke. 71 strokes were manually extracted of eight available data sets of data class 1. The strokes were randomly selected under consideration of the beginning, middle and end phase of the races. The start and end of a stroke was defined by the lowest point of the acceleration signal of each stroke. This correlates to the catch phase in the rowing motion (figure 1, overview of rowing stroke phases in [3]). The selected strokes were normalized to the same length, averaged and scaled to the maximum catch phase amplitude of all strokes. The resulting average stroke was used as template for the subDTW stroke detection.

2) subDTW stroke detection algorithm: Based on the subDTW algorithm as proposed in [7], [6], a stroke detection was implemented. Considering the acceleration of a rowing boat during a race, all strokes show similarity and can be segmented by the subDTW algorithm using the created template. It provides the start and end time of the detected stroke pattern, as well as an internally calculated quality factor $dtw_{quality}$. To adapt the algorithm to the specific rowing problem, a threshold $dtw_{threshold}$ of the quality factor had to be set to not allow poor detections in the algorithm output. Further, a minimum duration dtw_{min} of a detection was set to avoid too short strokes. Due to pretest results the threshold in this work was set to $dtw_{threshold} = 150$. This setting was necessary to avoid false positive detections of parts of the acceleration profile that show similarity to actual strokes. The minimum duration of a rowing stroke was estimated to $dtw_{min} = 1\ s$. Figure 1 shows the typical rowing acceleration signal and three strokes detected with the described algorithm.

3) Fragmental stroke rate calculation: Based on the detected rowing strokes in a specified period of time, the stroke rate can be calculated. The stroke rate s_{rate} in strokes per minute within the time t_{detect} can be calculated directly from the amount of detected strokes s_{amount} by

$$s_{rate} = s_{amount} \cdot \frac{60\ s}{t_{detect}[\text{in s}]}. \quad (1)$$

However, to accurately determine the stroke rate online during a race, the measurements would have to be executed at the exact end of a detected stroke. Otherwise, the measurement time t_{detect} contains parts of a stroke that are not considered in the calculation. In figure 1 this example is illustrated. To avoid this error, it is assumed that the partially visible strokes (before and after the completely detected strokes) follow the same pattern as the detected ones. Thus, the average length of the current rowing stroke $t_{stroke,av}$ is calculated. The proportion of the missed interval before and after the detected strokes $t_{missed} = t_{before} + t_{after}$ to the average stroke length $t_{stroke,av}$ indicates the amount of not yet calculated strokes. Equation 1 has to be modified to

$$s_{rate,mod} = (s_{amount} + \frac{t_{missed}}{t_{stroke,av}}) \cdot \frac{60\ s}{t_{detect}[\text{in s}]}. \quad (2)$$

For the verification of the fragmental stroke rate detection algorithm, the whole acceleration signal was segmented into windows. In order to avoid setting the windows always at the same position of a stroke the window size was varied randomly between 5 and 15 seconds. For the evaluation the number of detected strokes in the fragmented analysis was summed up over all windows and compared to the number of detected strokes in the whole signal.

C. Prediction of the rowing motion

Besides the accurate stroke rate calculation, a further application was established in this work: an algorithm to predict the rowing motion. The velocity signal is extrapolated and the upcoming position can be calculated.

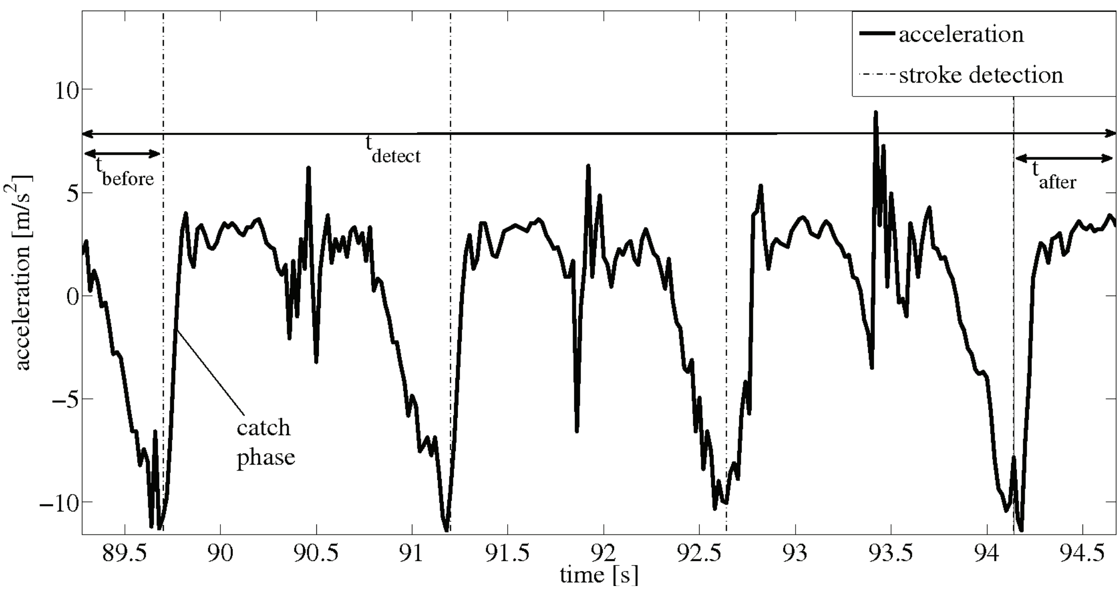

Fig. 1. Acceleration profile in rowing and subDTW stroke detection. The figure presents the typical acceleration signal during a race. The introduced subDTW algorithm correctly recognized the stroke pattern (dashed lines). The stroke rate calculation algorithm considers the three detected strokes in this example, but also the partially visible strokes before and after the detected ones.

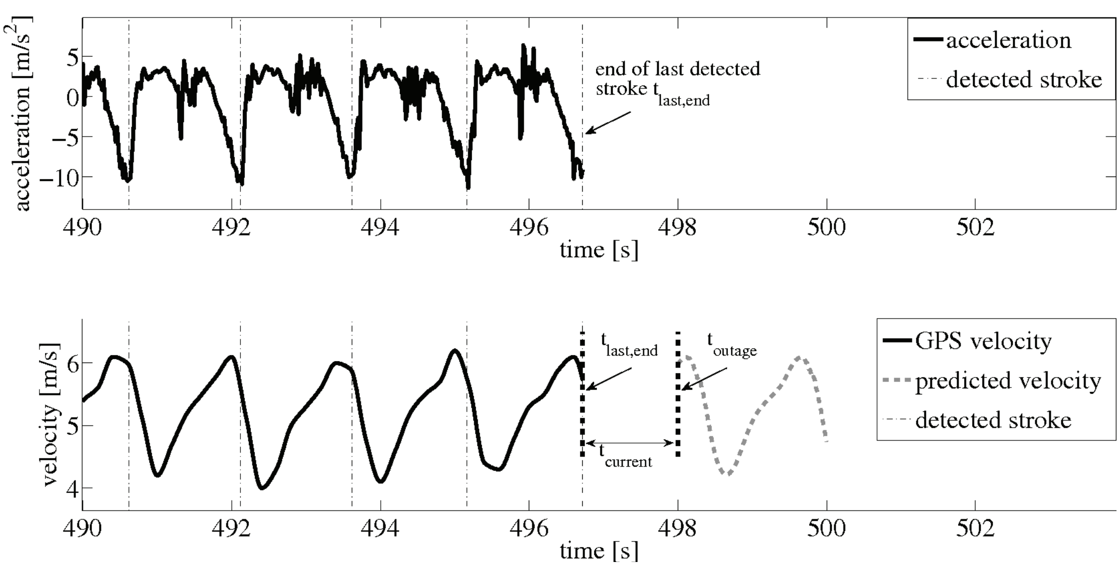

Fig. 2. Upper part: Stroke detection based on the accelerometer signal. The vertical lines represent the start/end of the detected strokes. Lower part: The detected strokes were transferred to the GPS measured velocity signal. The time between the end of the last step and the outage time step was calculated. The grey line illustrates the predicted velocity after the algorithm was executed.

1) Velocity prediction: The velocity prediction is based on the acceleration signal and GPS data before an outage occurs. Both are constantly transmitted to the land-based control station. In case of a transmission outage at t_{outage} the prediction algorithm starts running at the base station. The acceleration data of the past seconds is analyzed with the predefined template and the subDTW algorithm provides the start and end time of the last s strokes (Fig. 2, upper part). The time window that is analyzed depends on the number of strokes that should be used. In pretests an number of $s = 3$ strokes showed the best accuracy for the selected measurement environment and was set as a constant value. The thereby detected strokes are directly applied to the velocity signal (Fig. 2, lower part). It can be assumed that the velocity at a specific point of the stroke is similar to the velocity at the same point of the previous or upcoming stroke. To obtain the predicted velocity at the current time after the outage, the average of the measured velocity over the last s strokes is calculated. $t_{last,end}$ is defined as the time of the end of the last completely transmitted stroke. Based on the difference of t_{outage} and $t_{last,end}$, the current position $t_{current}$ at the stroke, respectively at the velocity pattern can be calculated by

$$t_{current} = t_{outage} - t_{last,end}. \quad (3)$$

Knowing the current state of the stroke execution and thereby the point in the velocity pattern, the current velocity can be obtained by observing the velocity curve progression (Fig. 3).

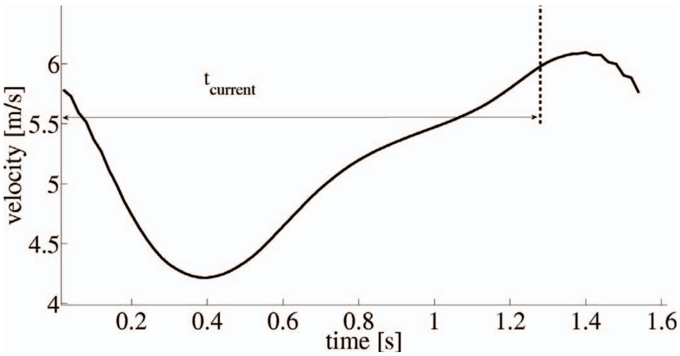

Fig. 3. GPS measured velocity of one stroke. The velocity prediction algorithm averages the velocity of the last strokes. The current position at the velocity curve is given by the time difference $t_{current}$ to the end of last detected stroke.

The resulting velocity prediction is demonstrated by the grey line in Fig. 2 (lower part).

2) Position calculation: After obtaining the velocity of the current time step $t_{current}$ the position $x_{current}$ can be estimated by integrating the velocity values since the last known GPS position $v_{GPS,last}$ over the sampling time dt. Assuming a 1-D-motion of the boat the driven trajectory is calculated by

$$x_{current} = x_{GPS,last} + \sum_{v=v_{GPS,last+1}}^{v_{current}} v(t) \cdot dt \qquad (4)$$

The evaluation was based on eight intervals (two intervals per evaluation data set) where transmission outages were simulated. It can be assumed that outages at certain positions of the stroke can easier be predicted than others. To avoid systematic evaluation errors, the lengths of the intervals varied between 10 and 20 seconds. Furthermore, outages were simulated constantly within the interval and not only at the beginning. Thus, at each sample point a new prediction was started. With a sampling time of 0.02 s (50 Hz), an average interval length of 15 seconds and four data sets, 6000 prediction tasks were evaluated.

The predicted velocity was evaluated by the correlation factor to the actual GPS measured velocity. The resulting position was compared to the RTK reference system. For both analyses outage/prediction times t_{pred} from 0.2 s to 20 s were executed.

III. Results

A. subDTW based stroke detection

The comparison with manually labeled acceleration signals showed a detection rate of 100% in the main part of the race for both data classes. Problems occurred in the first five seconds when the movement recently started. A maximum of three strokes after the start could not be detected. There was no false positive detection, neither in the beginning nor in the main part of the race.

B. Stroke rate calculation

The number of detected strokes by the fragmented analysis of the segmented signal and the total number of strokes over the whole signal is provided in table II for the four evaluated data sets. Compared to the detection over the whole race, the introduced algorithm shows an accuracy of more than 99%, averaged over three evaluation runs per data set. Assuming an average race time of 400 seconds and a window size of 5 to 15 seconds, there is an average of 40 windows per race and thereby 40 executions of the algorithm. Thus, the maximum summed up error of 2.3 strokes leads to an error of approximately 0.05 strokes per windows or 0.3 strokes per minute as stroke rate output. A typical stroke rate of rowing competitions is around 40 strokes per minute.

TABLE II. Result of stroke rate detection algorithm compared to the total number of strokes

race	total number	fragmental summed up	calculation accuracy
class 1 (I)	233	234.2	0.995
class 1 (II)	234	235.1	0.995
class 2 (I)	225	227.3	0.990
class 2 (II)	250	251.1	0.996

C. Velocity and position prediction

The predicted velocity after t_{pred} was compared to the actual GPS measured velocity. The correlation factor of the predicted and actual velocity is presented in figure 4 (black lines). The position output after integrating the predicted velocity was evaluated by the position output of the RTK reference system. The result is illustrated in figure 4 (grey lines). Both data classes were evaluated separately. Data class 1 is presented by continuous lines, data class 2 by dashed line. In addition, all results are provided in table III.

IV. Discussion and future work

The problem statement of this work was to find a stable method to predict the rowing motion based on the current and previous GPS data and acceleration signal. Therefore, a Subsequence Dynamic Time Warping algorithm was applied to the rowing motion in order to detect the rowing strokes by analyzing the acceleration signal. The first outcome of this algorithm was the actual method of predicting the rowing motion. The second outcome was the accurate determination of the stroke rate during races.

The subDTW stroke detection in the acceleration signal showed a high success rate after the first strokes of the race. The first 2 to 3 strokes of a race could hardly be detect because the acceleration profile showed a different behavior in the initial phase, starting from a state of rest. Later on, the algorithm could segment the acceleration signal in respect to the provided template of a stroke. However, a more sophisticated evaluation method has to be established to avoid the labeling of the acceleration signal. A video based validation could be used instead.

Furthermore, the evaluation with two data classes showed that the template for the stroke detection that was created of data class 1 also works for data class 2. The data classes represent different rowing classes. This leads to the conclusion that one template, averaged over all rowing classes, could be sufficient to detect the strokes in all professional rowing classes.

The detected strokes were used to calculate the stroke rate and to predict the rowing movement. The evaluation of the introduced fragmental stroke calculation showed the accuracy of the method in the analyzed data sets with an error of less

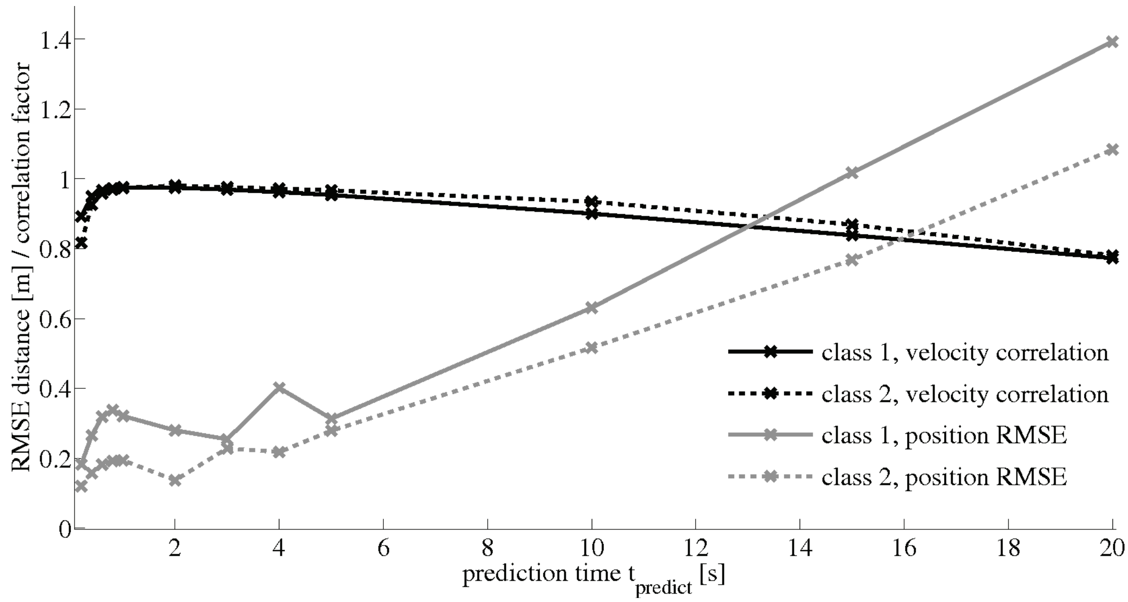

Fig. 4. Result of the velocity and position prediction of class 1 (solid lines) and class 2 (dashed lines). The black lines illustrate the correlation of the predicted and actual velocity. The RMSE of the predicted position offset to the reference position is presented in grey.

TABLE III. RESULT OF THE VELOCITY AND POSITION PREDICTION, ILLUSTRATED IN FIGURE 4

t_{pred} [s]	0.2	0.4	0.6	0.8	1	2	3	4	5	10	15	20
correlation factor (data class 1)	0.89	0.95	0.97	0.97	0.98	0.97	0.97	0.96	0.95	0.90	0.84	0.77
correlation factor (data class 2)	0.82	0.93	0.96	0.97	0.97	0.98	0.98	0.97	0.97	0.93	0.87	0.78
correlation factor (average)	**0.86**	**0.94**	**0.97**	**0.97**	**0.97**	**0.98**	**0.98**	**0.97**	**0.96**	**0.92**	**0.86**	**0.78**
position RMSE (data class 1) [m]	0.18	0.27	0.32	0.34	0.32	0.28	0.25	0.40	0.31	0.63	1.02	1.39
position RMSE (data class 2) [m]	0.12	0.16	0.18	0.19	0.19	0.14	0.23	0.22	0.28	0.52	0.77	1.08
position RMSE (average) [m]	**0.14**	**0.22**	**0.25**	**0.27**	**0.26**	**0.21**	**0.24**	**0.31**	**0.30**	**0.58**	**0.90**	**1.24**

than 1% compared to the analysis of the strokes rate over the whole race. Clearly, the assumption of partially available strokes before and after the detected ones only applies in cases of continuous motions, hence, during a race situation. A different method which only considers the actual detected strokes has to be developed for a more general stroke rate determination.

The evaluation of the prediction algorithm proved the ability of overcome transmission outages. The correlation between predicted and actual velocity was 78% for predictions up to 20 seconds and 96% for short time predictions up to 5 seconds. Slightly worse correlation factors for predictions of only 0.2 seconds might result from small deviations from the actual velocity that nevertheless strongly influence the correlation factor for short measurement times. The absolute position error resulted in 1.24 m for predictions up to 20 seconds and 0.30 m for 5 seconds predictions. As well as in the stroke detection algorithm no deterioration was determined by using the class 1 template for the class 2 prediction. The prediction results appear similar for both data classes.

The prediction system could be used for further applications in professional measurements. The final order of the boats could be estimated and the winner could be announced in time when passing the final line instead of analyzing the finish camera picture first.

The computation time of the implemented subDTW algorithm could be improved by using the Fast Incremental Dynamic Time Warping (FIDTW) of Horst [8]. However, the accuracy of the algorithm is not supposed to get any better as all labeled strokes were detected in the approach of this paper.

V. SUMMARY

The motivation of this work was given by the time measurement at rowing competitions and the occurring problems of potential data transmission outages. A Subsequence Dynamic Time Warping algorithm was implemented to detect the rowing strokes in the sensor signal. Based on this algorithm, two methods were established and evaluated: the fragmental stroke rate calculation during races and the algorithm to predict the movement in case of data outages.

The subDTW based stroke detection algorithm detected the strokes based on a predefined template. This template contained the typical acceleration profile of a rowing stroke. Using this stroke detection, the fragmental stroke rate calculation algorithm provided an accurate method for the online determination of the stroke rate during races. Furthermore, the detected strokes were used in the prediction algorithm. The start and end times of the detected strokes were applied to the GPS measured velocity signal. Processing the knowledge of the periodic stroke pattern in the velocity signal, the signal could be extrapolated. A position prediction was calculated by integrating the velocity data.

The evaluation of the system proved the function of detecting the stroke pattern in the acceleration signal. Compared to other systems, only one sensor unit was necessary. The algorithm worked robustly in all tested championship situations. The fragmental stroke rate calculation worked with an accuracy of more than 99%, compared to the calculation over the whole race. The prediction algorithm was evaluated with a position error of 30 cm for prediction times up to 5 seconds.

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