Optimization of Road Surface Wetness Classification Using Feature Selection Algorithms and Sensor Fusion

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ABSTRACT Due to the correlation between friction reduction and the road-covering water film height, knowledge about the current wetness level is of relevance for drivers and autonomous systems. A promising approach for wetness quantification is based on capacitive transducer arrays that enable to detect water spray ejected by the tires. Even though previous studies on this approach have shown the feasibility of wetness classification, optimization opportunities exist. While these previous investigations were limited to one feature selection algorithm, we study various algorithms and demonstrate the potential for optimization. Besides an application-specific algorithm that is capable of determining class-dependent features resulting in a performance improvement of more than 0.03 for the considered evaluation metrics, sequential forward floating selection in particular yields the most significant performance increase of more than 0.06. In addition, prior studies were limited to a test track with constrained conditions. Thus, in order to study the transferability of the preceding results, we present investigations on new experimental data acquired on public roads. The unknown and varying environmental conditions on public roads as well as a larger wheel speed range and steering angle effects are shown to significantly decrease classifier performance. We demonstrate that fusing two transducer arrays of different wheel arch liners increases performance by around 0.02. Here, a considerable information benefit can be attributed to the different transducer positions with design-related advantages. Furthermore, we show that the fusion with additional sensor data available in the vehicle results in a further performance improvement of more than 0.02.

INDEX TERMS Capacitive sensors, driver assistance, road surface wetness detection, vehicle safety, wetness classification.

I. INTRODUCTION Lower friction between a vehicle’s tires and the road surface increases the risk of accidents significantly under wet conditions [1], [2]. Here, the level of friction reduction correlates with the road-covering water film height [3], [4]. Thus, knowledge about the present wetness level is relevant to warn drivers or autonomous systems of potentially critical situations. Today’s vehicles already contain various technologies for environment perception, but these are not capable of detecting and quantifying road surface wetness.

In [5], we presented a novel approach for road surface wetness quantification. It is based on a 2 × 4-planar capacitive transducer array (TA) that is able to detect water ejected by the tires. In an experimental study on a test track, the reliable assessment of wetness-related dependencies with the proposed capacitive sensor system has been shown. Furthermore, we studied different classifier algorithms and evaluation metrics for data acquired on the test track. We presented a 1-nearest neighbor (1NN) classifier capable of automatically distinguishing between eight wetness levels with considerable performance.

With regard to the selection of suitable features, which provides several advantages over using the entire feature set, the
study in [5] was limited to the comparatively fast and simple sequential forward selection (SFS). As known from literature, no search strategy exists that can be preferred independently of the data set and further boundary conditions [6], [7]. Thus, we investigate whether the classification of road surface wetness using capacitive measurement data can be improved through feature selection algorithms. Besides implementing established algorithms from literature, we also propose an application-specific algorithm that is capable of determining class-dependent features.

Furthermore, while prior studies were limited to a test track with constrained conditions, we study the approach’s transferability to public roads for the first time. For that purpose, we present new experimental data acquired on public roads including higher wheel speeds and steering angles as well as unknown environmental conditions.

An optimization approach investigated in this paper comprises sensor fusion. As known from other applications, the consideration of additional sensor data can provide certain advantages including increased accuracy and certainty [8].

Current research on the fusion of sensor data in automotive applications particularly addresses environmental perception [9], [10]. The steadily increasing availability of sensor data offers new opportunities, which can also be of relevance to the field of road surface wetness classification. While other approaches in that field (see Section II) are limited to the individual measurement principles, we investigate whether additional sensor data available in the vehicle can improve classifier performance. In addition, we consider the fusion of sensor data from two TAs of different wheel arch liners.

The main contributions of this paper can be summarized as follows:

- We present a study on various feature selection algorithms in order to optimize an existing classifier for road surface wetness classification using capacitive measurement data.
- We propose an application-specific feature selection algorithm that is capable of determining class-dependent features.
- We present new experimental data and study the approach’s transferability to public roads for the first time.
- We propose a new setup of two transducer arrays from different wheel arch liners and investigate its potential.
- We present an investigation on the fusion of capacitive measurement data with additional sensor data available in the vehicle.

The remainder of this paper is structured as follows. Following our overview of related work in Section II, we give a brief overview of the underlying classifier along with relevant evaluation metrics for imbalanced data sets in Section III. Subsequently, in Section IV, a description of the experimental setup including the test vehicle, sensor system, and data acquisition conditions is given. Section V covers the feature selection algorithms. The application-specific algorithm is presented and a comparison is given. Afterward, we focus on the public roads data set and propose different optimization approaches using sensor fusion in Section VI. Subsequently, Section VII discusses the presented results. Finally, in Section VIII, a conclusion is drawn.

### II. RELATED WORK

Research on the detection of weather-related road conditions has covered a wide range of approaches. Besides studies on in-vehicle cameras [11], [12] research on radar sensors [13], [14] has become more relevant again, as these are part of the standard equipment of modern vehicles. While camera images enable differentiation between dry and snowy conditions, for radar technology a distinction between dry, wet, and icy conditions has been demonstrated. In particular, suboptimal lighting situations proved to be problematic for in-vehicle cameras and road surface roughness caused difficulties for radar sensors. Other approaches are based on acoustic methods. In addition to microphones that record the rolling noise of the tires [15], [16], [17], [18], acoustic sensors are used to detect the structure-borne noise of water drops impinging the vehicle body parts [19], [20]. The latest Porsche 911 (type 992) is equipped with these types of sensors. These can detect considerable wetness and warn the driver of possible aquaplaning [21], [22].

Another field that has been extensively covered in literature includes optical methods that exploit the spectral and reflective differences of water and ice to distinguish between road surface conditions [23], [24]. Based on this approach, commercial measurement systems are already available that allow road surface wetness quantification [25]. Due to their susceptibility to contamination, size, and price, they are not yet suitable for the automotive series application.

To our best knowledge, there is no research work related to the optimization of road surface wetness classification using feature selection algorithms. Thus, we consider established approaches from other applications. In this paper, we focus on wrapper methods that utilize a classifier as black box and evaluate different feature subsets regarding their performance [26]. While wrapper methods can be computationally intensive, they usually achieve high performance since feature selection interacts with the classifier and feature dependencies are taken into account [27]. Table 1 shows an overview of potential search strategies for feature selection.

#### TABLE 1. Overview of potential search strategies for feature selection.

| Strategy | Advantages | Disadvantages | Examples |
|----------|------------|---------------|----------|
| Optimal  | Optimal subset | Very high computational costs | ES, BAB |
| Greedy   | Simplicity, speed | Nesting effect | SFS, SBS |
| Floating | No nesting effect | Computational costs | SPS, SBS, TS |
| Stochastic | New feature combinations | Bias required | SA, GA |
| Weighted | Feature relevance inclusion | Overfitting | TSPW |

Additionally, the field of sensor data fusion in automotive applications particularly addresses environmental perception. As known from other applications, the consideration of additional sensor data can provide certain advantages including increased accuracy and certainty [8].

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with advantages and disadvantages as well as examples of established algorithms.\(^1\)

Optimal search strategies are able to identify the optimal feature subset, but are computationally very intensive and therefore only applicable to small feature sets [7]. These strategies include exhaustive search (ES) and the branch-and-bound (BAB) algorithm, as well as its variations [6]. Due to their simplicity and speed, greedy search strategies are often used instead. Common examples are SFS and sequential backward selection (SBS). Basically, these algorithms follow the strategy of successively improving an evaluation criterion by adding or removing features, respectively. Since features already added in SFS or removed in SBS are not considered further, both algorithms may be trapped in local optima, known as the nesting effect [28].

Floating search strategies attempt to avoid the nesting effect. Two examples are sequential forward floating selection (SFFS) and sequential backward floating selection (SBFS), which are extensions of SFS and SBS [28]. The greedy search strategies are modified to allow backward steps. For SFFS, features that have already been selected can be back-excluded using SBS, and for SBFS, features that have previously been excluded can be back-included using SFS. Another familiar example is tabu search (TS) which is a meta heuristic and associated with lower computational costs [29], [30]. In contrast to the previous algorithms, TS allows intermediate steps that initially result in poorer classifier performance, with the intention to bypass local optima. A short-term memory called tabu list is used that records and guides the search process.

Stochastic strategies are characterized by the ability to leave local optima by randomly allowing temporary deterioration of the evaluation criterion [6]. However, they require biases which can significantly affect the search as well as the performance [31]. Simulated annealing (SA), which is based on the analogy of cooling a substance to its low temperature equilibrium, is a popular example [27]. SA allows minor and random modifications to the subset that are accepted using a time-dependent probability. Another well-known example are Genetic algorithms (GAs), whose search strategy is derived from evolution [7].

In weighted search strategies, weights are assigned to the features depending on their relevance to the class decision [26]. Feature weighting (FW) can be realized in combination with the search strategies introduced before. An example is represented by tabu search with feature weighting (TSFW) which is an extension of the previously introduced algorithm [30]. However, FW can result in an increasing probability of overfitting.

### III. PRELIMINARIES - WETNESS CLASSIFICATION

The \(1\)NN classifier with Euclidean distance metric is a suitable learning algorithm for classifying road surface wetness levels [5]. In order to predict a class, \(1\)NN identifies the point in training data with smallest distance to the test sample to be assigned. Equal to most learning algorithms, \(1\)NN assumes a balanced class distribution and equal misclassification costs [32], [33]. In order to handle imbalanced data sets as well, various solutions have been proposed in literature. For road surface wetness classification, the use of an adequate metric for classifier evaluation and identification of suitable features has been shown to be an appropriate approach [5].

The metrics are applied to prevent small classes from being predicted incorrectly more frequently. The balanced accuracy (BAC) is a commonly used metric that can take values in the range of \([0, 1]\), where 1 represents the perfect classification. It is defined as the recall obtained of each class averaged over the number of classes [34]

\[
BAC = \frac{1}{K} \cdot \sum_{i=1}^{K} \text{recall}_i, \tag{1}
\]

where \(K\) is the number of classes. The recall, which describes the proportion of positive labeled cases correctly classified, is defined as

\[
\text{recall}_i = \frac{TP}{TP + FN}, \tag{2}
\]

where \(TP\) represents the number of correctly predicted positive labeled cases (true positive) and \(FN\) the number of positive cases misclassified as negative cases (false negative). Since we assume misclassifications to adjacent classes (see Table 2) as less safety relevant, we extend the classes’ recall by an additional weighting factor

\[
\text{recall}_i^* = \text{recall}_i \cdot \frac{TP + \frac{1}{2} \cdot \Phi (FN)}{TP}, \tag{3}
\]

where \(\Phi (FN)\) represents the number of false negatives in adjacent classes. Here, misclassifications between dry and damp\(_1\) are not considered in \(\Phi (FN)\). According to eq. 1, BAC is also expanded to

\[
BAC^* = \frac{1}{K} \cdot \sum_{i=1}^{K} \text{recall}_i^*. \tag{4}
\]

#### TABLE 2. Assignment of road surface wetness levels and water film thickness \(t_w\).

| Road wetness | Class   | Water film thickness \(t_w\) |
|--------------|---------|----------------------------|
| Dry          | Dry     | 0 mm \(\leq t_w < 0.01\) mm |
| Damp         | Damp\(_1\) | 0.01 mm \(\leq t_w < 0.05\) mm |
|              | Damp\(_2\) | 0.05 mm \(\leq t_w < 0.10\) mm |
| Wet          | Wet\(_1\) | 0.10 mm \(\leq t_w < 0.20\) mm |
|              | Wet\(_2\) | 0.20 mm \(\leq t_w < 0.30\) mm |
|              | Wet\(_3\) | 0.30 mm \(\leq t_w < 0.40\) mm |
| Very wet     | Very wet\(_1\) | 0.40 mm \(\leq t_w < 0.50\) mm |
|              | Very wet\(_2\) | 0.50 mm \(\leq t_w\) |

\(^1\)The algorithms are briefly described here. For a more detailed description of the algorithms please refer to the given literature.
BAC has proven to be a suitable evaluation metric as well as optimization criterion for identifying appropriate features by SFS from our set with 593 features.

IV. EXPERIMENTAL SETUP
This section outlines the experimental setup. In addition to the test vehicle, the sensor system, as well as data acquisition conditions are presented.

A. TEST VEHICLE
The test vehicle is a Porsche 911 (type 991.2 Carrera 4 GTS) with 20" 245/35 winter tires on the front axle, which have a tread depth of approximately 6 mm and an asymmetric tread pattern. The vehicle is equipped with a reference measuring system (Lufft, MARWIS) for determining current road surface wetness. It is commonly used as decision support for airports and winter services and can measure water film thickness with non-invasive optical spectroscopy in a range from 0 to 6 mm. It provides a resolution of 0.1 µm, a precision of ±10% and a sampling rate of 100 Hz [25]. For the experimental study, MARWIS is connected via controller area network (CAN) and integrated into the vehicle’s front trunk, which is equipped with an opening to the road. Thus, reference data can be recorded synchronous to data from the sensor system (see Section IV-B) and data from the vehicle bus (e.g., wheel speed). Since the opening is located in the vehicle’s center, MARWIS’ limited sensing area just covers the road surface horizontally shifted to the tire track. Therefore, small deviations regarding the precise water film thickness in the tire track may occur.

B. SENSOR SYSTEM
The test vehicle is equipped with two capacitive sensor systems each comprising a transducer array and sensor electronics. The individual components are described below.

1) TRANSDUCER ARRAY
A 2 × 4-planar capacitive TA is capable to detect water spray ejected by the tires and its wetness-related dependencies [5]. For the data acquisition in this paper, two TAs are applied on the front wheel arch liners’ rear-facing sides as spray impinges on these first providing a faster decision. Due to the tires’ displacing characteristics that lead to modified conditions for the rear wheels causing disadvantages for especially low road surface wetness levels, both TAs are applied on the front wheels. In addition, we assume the different vehicle sides’ TAs complement each other well for steered wheels.

The individual transducers are manufactured as flexible printed circuit boards (PCBs) of size 54 × 54 × 0.2 mm³. Due to their low thickness, they can be applied almost planarly without significantly affecting the impinging and draining droplets’ characteristics. Fig. 1 (a) shows the arrangement of the eight transducers for the left (TA_l) and the right (TA_r) array as a front view divided into horizontal (HPs) and vertical positions (VPs). While the left TA comprises three electrode designs (EDs), the right TA includes two. The detailed layering of the transducers, as well as the parameterization of the individual complementary EDs, corresponds to the description given in [35]. In brief, ED_1 provides the highest dynamic range and sensitivity for low amounts of water, whereas ED_2 is supposed to allow detection of larger quantities. ED_3 on the other hand has the highest penetration depth and is designed to distinguish very large amounts of water. For more details on the EDs, which are out of the scope of the paper, please refer to [35].

2) SENSOR ELECTRONICS
For reliable acquisition of the capacitive measurement data, application-specific sensor electronics are used, which are mounted in waterproof housings behind the wheel arch liners as shown in Fig. 1 (b). FDC2214 [36] represents the core component of the sensor electronics for recording and digitizing the capacitances. For this purpose, the capacitance-to-digital converter (CDC) uses LC resonators which are tuned to 100 kHz for data acquisition. In addition, the sensor electronics include a temperature sensor, a 32bit microcontroller and a CAN transceiver. The measurement data of the individual transducers are transmitted as int16 data type via CAN bus, resulting in a theoretical value range of −3276.8 pF to 3276.7 pF with a resolution of 0.1 pF and a sampling rate of 145 Hz.

TABLE 3. Class-specific sample numbers of the data sets.

| Index | Class     | Number of samples |
|-------|-----------|-------------------|
| 1     | Dry       | 7,812             | 460                |
| 2     | DampP1    | 2,301             | 3,565              |
| 3     | DampP2    | 800               | 2,667              |
| 4     | WetP1     | 811               | 2,441              |
| 5     | WetP2     | 394               | 1,429              |
| 6     | WetP3     | 271               | 1,139              |
| 7     | Very wetP1| 185               | 1,094              |
| 8     | Very wetP2| 98                | 1,202              |
| Total |           | 12,672            | 13,997             |
C. DATA ACQUISITION

The database for the studies within this paper is subject to two different degrees of complexity. Besides data collected on a test track at defined and reproducible conditions, data is acquired under random conditions on public roads. The two cases are described subsequently.

1) TEST TRACK

Data collection is performed at three different wheel speeds (15 kph, 30 kph and 50 kph) on a 445 m long asphalt circuit with two longer straight sections. Over a length of approximately 60 m, one of these straight sections can be watered (σ ≈ 400 μS/cm) manually. Therefore, effects on the sprayer’s characteristics induced by steering can be neglected. Due to the asphalt’s characteristics and the water displacement by the tires, wetness levels can not be kept stable. Thus, the test track is watered at the beginning of a defined number of test runs. During these continuous runs, the test track dries to a degree sufficient to cover all defined levels of wetness (see Table 2).

Considering the sensor system’s sampling rate (see Section IV-B), data is split up into segments of 150 sample points and assigned to one of the eight classes from Table 2. Under the given conditions, higher wetness levels in particular are difficult to generate. This results in the imbalanced data set, summarized in Table 3, containing a total of 12,672 samples.

2) PUBLIC ROADS

Data acquisition is performed over seven different days with precipitation at temperatures between 2°C and 15°C on public roads in Germany. Due to varying rain intensity and duration, all defined wetness levels are covered, as shown in Table 3. In contrast to the data from the test track, class dry is underrepresented as a result of precipitation. Furthermore, the samples cover a wider range of wheel speeds by 10 kph ≤ v ≤ 250 kph with more than 54% occurring in the range between 110 kph ≤ v ≤ 130 kph. Moreover, those speeds characteristic of urban roads, which have been in focus on the test track, are underrepresented at about 7%. In addition, the samples include steering angles in the range of approximately −30° ≤ δR ≤ 30°.

Besides wheel speed and steering angle, another significant factor worth mentioning is the electrical conductivity of water which can affect capacitance and thus, potentially complicate wetness classification. While the water’s conductivity has been assumed to be approximately constant on the test track, significant deviations can occur under realistic conditions. Zdebski et al. [37] report conductivity median values in the range of 1 μS/cm ≤ σ ≤ 26 μS/cm for harvested rainwater from air as well as roof coverings and Yaziz et al. [38] in the range of 6 μS/cm ≤ σ ≤ 33 μS/cm for rainwater collected from open ground. In addition, vehicular and road contaminants can be expected to increase the conductivity of water, due to additional free charge carriers in the form of ions [39]. Studies by Makineci et al. [40] on forest roads showed fluctuations in the range of approximately 50 μS/cm ≤ σ ≤ 200 μS/cm. In the extreme scenario, for contamination with road salt, conductivity of several mS/cm is realistic.

V. FEATURE SELECTION ALGORITHMS

In general, the feature set’s individual features are of varying importance for class prediction. They can correlate with each other and be counterproductive to the decision process [41]. A reduction of features is often desirable and referred to as feature selection. In literature, feature selection has been motivated variously and provides several advantages over using the entire feature set [27], [42]. Besides a significant reduction of training time as well as complexity by excluding correlated and counterproductive features, especially the potential increase of classifier performance has to be mentioned as a key advantage [43], [44].

As shown in the overview on feature selection algorithms (see Section I), a variety of search strategies with different advantages and disadvantages are available for finding a suitable feature subset. Despite several comparative studies with respect to the algorithms’ performance, no search strategy exists that can be preferred independently of the data set and further boundary conditions [6], [7]. Therefore, different algorithms are generally evaluated for a given problem. In principle, a pre-selection is possible based on the boundary conditions and requirements. For the present problem, especially the large feature set is a criterion that leads to excluding some algorithms listed in Table 1. In this paper, except for the optimal search strategies, at least one suitable algorithm is implemented from each category under consideration of the characteristics and evaluated with respect to a potential optimization of the classifier’s performance. Furthermore, we introduce a problem-specific algorithm.

In addition to the use of an application-specific optimization criterion for assessing suitable features, successfully implemented in [5], modifying the search strategy is another possibility for the consideration of imbalanced data sets [45], [46]. From text categorization, an approach is known which determines suitable features for positive as well as negative classes separately and combines them afterward to a feature set [47]. Within this paper, we follow a similar approach, which is extended problem-specifically and merges different strategies. Fig. 2 shows the flow chart of the algorithm referred to as class feature selection (CFS) below. Assuming an empty feature subset \( M_i \), an individual subset \( M_i \) is iteratively determined for each of the K classes \( c_i \). For this purpose, an SFS is performed for each class while optimizing the class-specific recall\(^*\) (see eq. 3). Finally, redundant features are eliminated from the merged subsets by SBS under optimization of the BAC\(^*\) (see eq. 4) to determine a final subset.

In order to evaluate the implemented algorithms for the given problem, the data set acquired on the test track...
(see Table 3) is considered and a 1NN classifier under optimization of \(BAC^*\) for \(TA_r\) is applied consistently. Since the implemented search strategies are suboptimal, each algorithm is studied tenfold to increase the results’ confidence. In addition, we use tenfold cross-validation, which involves randomly dividing the data set into ten folds of approximately equal size, for feature selection and subsequent evaluation. Table 4 summarizes the arithmetic mean and the iteration with the highest classifier performance for each algorithm. Besides \(BAC^*\), \(BAC\) as well as the number of selected features are shown for comparison.

Except for SA, all implemented algorithms can increase classifier performance, in both the mean as well as the best run, compared to the previously used SFS which is characterizedly trapped in local optima. The most consistent results over ten iterations can be obtained with TS, reaching the highest classifier performance on average and increasing \(BAC^*\) to over 0.95. Here, no advantages are shown by feature weighting (TSFW). However, the performance increase is accompanied by a fivefold increase with respect to the required number of features. On the other hand, SFFS can obtain the most significant performance increase for the best run. The \(BAC^*\) can be increased by more than 0.06 to over 0.98, with only a slight rise in the number of selected features. SFFS is also dominant compared to the other algorithms, outperforming them by more than 0.02 in \(BAC\) as well as 0.04 in BAC. In addition, the number of selected features is concordantly smaller. However, as the results averaged over ten iterations show, SFFS is subject to variations in both classifier performance and number of selected features, which can be attributed to the algorithm’s suboptimal search properties and demonstrates the benefits of repetitive searches. Furthermore, the introduced CFS can also achieve a high performance improvement with a \(BAC^*\) of almost 0.96 at 34 features. Thus, class-specific feature selection is another alternative to handle imbalanced data sets, even if SFFS is the dominant search strategy under optimization of \(BAC^*\) for the present problem.

### VI. SENSOR FUSION

In order to evaluate the significance of the increased complexity level due to the given boundary conditions on public roads (see Section IV-C), a classifier is initially developed based on the derived parametrization from previous investigations. Analogous to Section V, a 1NN classifier with SFFS under optimization of \(BAC^*\) for transducer array \(TA_t\) is evaluated in ten iterations for comparison. Tenfold cross-validation is used for feature selection and subsequent evaluation. Table 5 summarizes the results for the two data sets acquired on the test track and public roads.

The underlying conditions result in a significant decrease of classifier performance. While the best performing SFFS for the data set acquired on the test track achieves a \(BAC^*\) of more than 0.98, it decreases by almost 0.19 for the current data set. Fig. 3 shows the class-specific recall, \(\text{recall}_i\), and \(\text{recall}^*_i\) as well as the resulting \(BAC\) and \(BAC^*\) of the best-performing feature subsets determined by SFFS for both data sets. For the test track data, a recall of 0.95 and a \(\text{recall}^*\) of 0.97 can be exceeded in each class. This results in a largely balanced and very high classifier performance with a \(BAC\) of more than 0.97 as well as a \(BAC^*\) above 0.98 for the eight classes. The extended boundary conditions on public roads, on the other hand, lead to different results. In particular, classes 5-7 show low recalls in the range of 0.51 to 0.56. Furthermore, the individual classes benefit significantly from the application-specific extension of the recall. This suggests that a large proportion of misclassifications are related to adjacent classes. Besides the larger wheel speed range, the
FIGURE 4. Flow chart of the forward transducer selection.

TABLE 6. Performance (BAC*) history of the FTS considering the single iterations and selected transducers for the data set acquired on public roads.

| i | R_{10} | R_{11} | R_{13} | R_{23} | L_{12} | L_{22} | L_{24} |
|---|--------|--------|--------|--------|--------|--------|--------|
| 1 | 0.6445 | 0.6688 | 0.6408 | 0.6153 | 0.6023 | 0.6474 | 0.6336 |
| 2 | 0.7336 | -      | 0.7278 | 0.7342 | 0.7165 | 0.7304 | 0.7494 |
| 3 | 0.7824 | -      | 0.7674 | 0.7751 | 0.7576 | 0.7700 | -      |
| 4 | -      | 0.7879 | 0.7905 | 0.7897 | 0.7965 | -      | -      |
| 5 | -      | 0.8068 | 0.8090 | 0.7963 | -      | -      | -      |
| 6 | -      | 0.8082 | -      | 0.8134 | -      | -      | -      |
| 7 | -      | 0.8150 | -      | -      | -      | -      | -      |

A performance decrease can be attributed to the unknown as well as varying environmental conditions (see Section IV-C) which lead to larger overlaps of the measured capacitances and, especially in the range of medium wetness levels, to differentiation problems.

As shown by the results, there is a potential for optimization regarding the data set generated on public roads. With respect to classifier optimization, below we address the research question of whether the consideration of a second wheel arch liner as well as additional sensor data available in the vehicle can improve road surface wetness classification. In addition, we analyze different class granularities that can be chosen depending on the potential use case.

A. FUSION OF TWO TRANSDUCER ARRAYS

In order to evaluate the relevance of simultaneously using two TAs, the features applied in the previous part of the paper (see Section III) are generated for transducer array TA\_r in addition to TA\_l. This results in a total of 1,185 features for the 16 transducers. Furthermore, in order to study the significance of a second TA and its individual transducers, a forward transducer selection (FTS) is performed which successively selects transducers that achieve the highest classifier performance when combined. For this purpose, the feature set is divided into transducer-dependent subsets and the algorithm shown in Fig. 4 is implemented using the 1NN classifier with BAC* as optimization criterion as well as tenfold cross-validation. Starting from a blank transducer selection and 16 feature subsets, each remaining set is combined individually with the current selection and ten SFFSs are performed respectively. After the best performing classifier is determined, it is tested whether the BAC* improved compared to the current selection. An improvement results in the addition of the corresponding transducer. If the performance cannot be improved or if all transducers have been included, the algorithm ends.

Table 6 shows the results of the FTS for the selected transducers. The positions (see Fig. 1) of transducer array TA\_r are represented by R_{xz} and those of TA\_l by L_{xz}. A total of seven different transducers are selected, four being assigned to TA\_r and three to TA\_l. The selection alternates between the vehicle sides allowing to deduce a significant information gain from the different integration positions. Furthermore, all vertical positions are already considered after five iterations indicating their importance. Moreover, design-dependent advantages arise for ED\_1, which is selected on five positions, for the present data set. ED\_3, on the other hand, which has been designed in particular for very large droplet sizes and quantities (see Section IV-B), is not considered. Overall, a BAC* of approximately 0.82 can be achieved with 33 selected features of seven transducers. Thus, the classifier performance can be significantly increased by fusing two transducer arrays of different wheel arch liners in comparison to a single-sided solution.

B. CONSIDERATION OF ADDITIONAL SENSOR DATA

Having shown that classifier performance can be significantly increased by the fusion of two TAs of different wheel arch liners, this section investigates the significance of additional sensor data available in the vehicle with respect to classifier performance. For this purpose, the feature set from Fig. 5 is considered. Analogous to the previously used wheel speed, the temperature inside the wheel house, recorded with the sensor electronics introduced in Section IV-B, is additionally considered in the generation of features related to the capacitance. Furthermore, similar features are generated independently of the capacitance vectors for the amount of precipitation detected by a rain sensor, which does not allow direct conclusions to be drawn about the current road surface wetness, but represents a potential complement. In addition, the wiper speed, which is correlated to the precipitation amount, is considered as a feature. Moreover, steering wheel angle, road unevenness, and road surface temperature are considered in the feature set which includes a total of 1,428 features.

4 For the present data set with precipitation in 61% of the test drives, an individual study of the rain sensor with 1NN classifier and tenfold SFFS is applied. The best performing SFFS yields a BAC of about 0.26 and a BAC* of approximately 0.38, considering the eight classes from Table 2.
TABLE 7. Performance of the classifiers $K_{F,K_C}$ with fused feature set in comparison to the classifiers $K_{0,K_C}$ with original feature set for the data set acquired on public roads.

| Classifier    | BAC* mean | BAC best | Features mean | BAC best |
|--------------|-----------|----------|---------------|----------|
| $K_{F,2c}$  | -         | -        | 0.9519        | 0.9595   |
| $K_{0,2c}$  | -         | -        | 0.9332        | 0.9460   |
| $K_{F,4c}$  | -         | -        | 0.8707        | 0.8749   |
| $K_{0,4c}$  | -         | -        | 0.8454        | 0.8514   |
| $K_{F,8c}$  | 0.8287    | 0.8381   | 0.7348        | 0.7483   |
| $K_{0,8c}$  | 0.7953    | 0.7970   | 0.6902        | 0.6937   |

**FIGURE 6.** Proportions of selected features for the most performant classifiers from Table 7.

Analogous to the previous investigations, the realization of the classifier $K_{F,8c}$, which differentiates into eight wetness levels, is realized by 1NN algorithm and individual SFFS with BAC* as optimization criterion. Furthermore, two classifiers with coarser class granularity are implemented. Besides classifier $K_{F,4c}$, which assigns the feature vector $x_i$ a class $y_i \in C_{4c} = \{c_{dry}, c_{damp}, c_{wet}, c_{v+wet}\}$, a binary classifier $K_{F,2c}$, which distinguishes between dryness and wetness, is developed. Here, the correction factor for misclassification into adjacent classes is neglected resulting in the realization of individual SFFSs with BAC as optimization criterion. For feature selection and subsequent evaluation tenfold cross-validation is used. Table 7 summarizes the results for ten SFFSs respectively, where $K_{0,K_C}$ represents the initial classifier without a fused feature set.

As shown in Table 7, classifier performance can be significantly increased by using the fused feature set. For example, the classifier $K_{F,8c}$ achieves a BAC* of approximately 0.84 for the best performing SFFS. In addition to an increase of over 0.04 compared to $K_{0,8c}$ this also corresponds to an increase of more than 0.02 compared to the classifier from Table 6 which has been realized from the fused feature set of the two TAs. That significant increase in classifier performance can be attributed to the additional features. Fig. 6 plots the number of selected features for the best performing classifiers with respect to the underlying data vector. As the figure shows, features of all additional data vectors from Fig. 5 are considered for classifier $K_{F,8c}$. A significant amount is attributable to capacitance features related to temperature, that may have an impact on absolute capacitance.

Furthermore, features related to precipitation, road unevenness as well as the steering wheel angle complement the capacitive features and have a contribution to the increased classifier performance.

Analogously, the performance of the classifiers $K_{F,4c}$ and $K_{F,2c}$, which obtain considerable BACs for the present data set, can be significantly increased by the additional features. Here, the decreasing class granularity results in a reduction of features that can be attributed to supplementary data vectors. All in all, the results consistently show a significant increase of classifier performance by considering additional sensor data available in the vehicle.

VII. DISCUSSION

While previous studies on the approach focused on evaluation metrics, classifier algorithms as well as the individual features, this paper has shown the importance of a suitable feature selection algorithm for a reliable road surface wetness classification. The performance gain of more than 0.06 using SFFS in comparison to the SFS from the prior study is quite significant and shows the optimization potential of feature selection algorithms with respect to wetness classification. Also, beyond the capacitive approach, the approaches presented in Section I that are not using deep learning may benefit from the results, as these have not yet addressed feature selection algorithms. In this context, the proposed CFS should also be mentioned. Beyond the application, this class-specific selecting algorithm also offers potential for multi-class applications and imbalanced data sets. Furthermore, the algorithm (see Fig.2) could be adapted by replacing the SFS with the SFFS potentially resulting in an optimization.

The contribution made in terms of transferability to public roads is also important for the field of road surface wetness classification. So far, the approach had only been investigated and evaluated under known environmental conditions on a test track. Furthermore, the investigations were limited to straight sections as well as moderate wheel speeds. Although the higher complexity due to unknown and varying environmental conditions on public roads results in a significant performance decrease, a BAC* of approximately 0.8 for eight classes is still considerable. In particular, optimization is conceivable from the data set point of view. The wheel speeds might be covered more comprehensively and the significant underrepresentation of the dry class should be addressed.

The results on fusing two TAs of different wheel arch liners have shown that further optimizations are possible. The additional information of the second vehicle side offers advantages and can significantly optimize the system. Furthermore, the results show that a reduction of the applied transducers is a possibility. For example, an implementation of four transducers per front wheel arch liner would be feasible. An optimization option might be the use of additional TAs on the rear wheel arch liners. While these positions generally have drawbacks as single TA solution, they could potentially provide complementary information.
While previous work has only considered the wheel speed as supplementary information, the consideration of additional sensor data available in the vehicle offers further optimization potential as the results have shown. The approach presented in this paper, considering a limited amount of additional data, has already resulted in a significant performance increase. Thus, an even larger performance improvement can be expected with the inclusion of further suitable sensor data, also applicable for other detection methods from Section I. In this context, a combination of the capacitive approach with other approaches that are limited to the distinction between water, ice and snow might be a promising topic for future research.

VIII. CONCLUSION

In this paper, we studied different approaches for the optimization of road surface wetness classification using capacitive measurement data. As prior work was limited to one feature selection algorithm, an investigation included further algorithms and demonstrated the potential for optimization. While the proposed CFS improved classifier performance by more than 0.03 for the considered evaluation metrics, SFFS yielded the most significant performance increase of more than 0.06. Furthermore, we investigated the transferability of results obtained for data acquired on a test track to data generated on public roads. Due to the increased complexity arising from the unknown and varying environmental conditions as well as a larger wheel speed range and steering angle effects, classifier performance significantly decreased. In addition, we demonstrated further potential for optimization by fusing two transducer arrays of different wheel arch liners. Here, a significant information gain could be attributed to the different transducer positions with design-related advantages resulting in a performance improvement of approximately 0.02. Moreover, we demonstrated that consideration of additional sensor data available in the vehicle results in a further increase in classifier performance by more than 0.02. The selected class granularity affects the performance as well as the number of required features and can be chosen according to the requirements. Overall, the findings presented in this paper can significantly contribute to a reliable classification of road surface wetness.

APPENDIX A

ABBREVIATIONS AND ACRONYMS

Table 8 provides a list of the abbreviations and acronyms used.

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