2009 American Control Conference
Hyatt Regency Riverfront, St. Louis, MO, USA
June 10-12, 2009

Driving Skill Recognition: New Approaches and Their Comparison

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Abstract— **Driving skill characterization is an important step towards future enhancement of vehicle adaptation control and active safety. This paper presents new approaches for driving skill recognition and their comparison. New feature extractors based on wavelet transform are developed to include temporal (spatial) information into discriminant features. The extractors are integrated with three classifiers for evaluation. Results show advantages of new approaches over existing approaches.**

I. Introduction

In order to tune vehicle control parameters for personal preference and active safety, it is prerequisite to know a driver's skill level. Growing interest has been expressed towards the application of pattern recognition methods to driving skill characterization [1-2]. The basic idea of this technique is two-fold. First an extractor is needed to extract discriminant features from a set of data, e.g. a sampled steering wheel angle signal. The discriminant features reflect the dissimilarity between drivers with different skill levels. Second classifiers are used to collect the features from the extractor and intelligently identify the skill level of a driver.

In [1] Discrete Fourier Transform (DFT) coefficients of steering wheel angle signals normalized at a certain speed offer a discriminant feature to differentiate drivers. A Feed-Forward Neural Network (FNN) is then used to construct an FNN-based classifier. In [2] further investigation on other classification methods such as Decision Tree and Support Vector Machine (SVM) has been conducted. It is concluded in [2] that the SVM-based classifier outperforms the FNN-based classifier and the Decision-Tree-based classifier in terms of the highest correct recognition rate among them.

Between feature extraction and feature classification, the former part is more fundamental and more critical to driving skill recognition, because even if there were a perfect feature classification algorithm with 100% accuracy, without a good discriminant feature, the correct recognition rate would not be as good as expected. In [1-2], the DFT technique has been applied to feature extraction. The essence of DFT feature extraction is to conduct DFT to capture the spectral characteristics of a feature signal and to use the resulting DFT coefficients as a discriminant feature to separate skillful drivers from typical drivers. However we know that driving behaviors explicitly exhibit temporal characteristics. It would be beneficial to incorporate temporal information, in addition to spectral information, into feature extraction. In this paper, we apply Wavelet Transform (WT) to steering wheel angle signals so as to combine spectral information and temporal information (equivalent to spatial information when signals are normalized with speed) into one feature extractor. The use of temporal information leads to an improvement of feature extraction and in turn the overall performance for driving skill recognition. The new feature extractor will be assessed with three classifiers: a new Radial-Basis-Network-based (RBN) classifier and the SVM-based and FNN-based classifiers proposed in [1-2].

The data for analysis and experiments are from the same dataset used in [1-2], which is collected via a driving simulator for constant-speed limit-handling maneuvers. There are totally 12 drivers in the dataset. Four of them are considered as skillful drivers and the rest are categorized as typical drivers according to a survey conducted before their tests. The maneuver discussed in this paper is double-lane change (DLC). Since each driver has participated in multiple test runs, there are totally 403 successful runs, consisting of 178 runs of skillful drivers and 225 runs of typical drivers.

II. Wavelet-Based Feature Extraction

Various techniques based on spectral analysis have been developed for signal analysis, control systems, and pattern recognition. The most well known technique of these is Fourier analysis. As Fourier analysis transforms a signal from the time domain into the frequency domain, the temporal (spatial) information of the signal will be lost. On the other hand, the most significant information for a driver is the road information collected via his vision. The driver's response to spatial information is critical for driving skill recognition. A common sense is that a skillful driver acts more promptly than a typical driver based on the observation of roads and his positions. This is an important and useful discriminant feature, which Fourier analysis cannot detect.

A way to correct the deficiency of Fourier analysis is to analyze only a small section of a signal at a time and reflect the original signal on a two-dimensional map of time (or space) and frequency. Methods such as Short-Time Fourier Transform (STFT) and Wavelet Transform (WT) have been introduced for this purpose. A drawback of STFT is that a time window of a certain size has to be determined in advance. The pre-determined time window is not suitable for driving skill recognition because how to choose the window size for the best performance is unknown, especially when the speed varies for each run. As a more flexible method, WT meets our expectation as it allows the use of longer time windows for lower frequencies and shorter time windows for higher frequencies by exploiting a set of wavelets.

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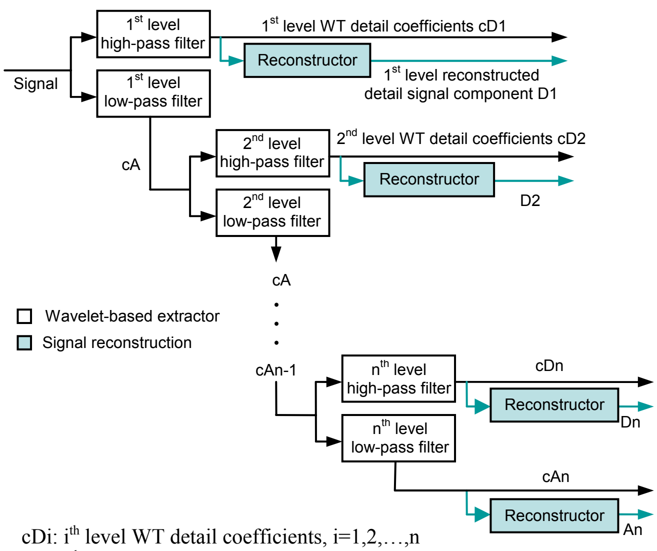
978-1-4244-4524-0/09/$25.00 ©2009 AACC

Several families of wavelets, such as Haar, Daubechies, Biorthogonal, Coiflets, [3-7], have been successfully applied to signal analysis, image processing, and fault detection. Continuous WT (CWT) that calculates wavelet coefficients at each scale and position is impractical, because it provides highly redundant information, requiring a huge amount of computation resource. Discrete WT (DWT) gives sufficient information for analysis and synthesis of the original signal, and offers a more efficient and practical way to operate WT. Readers can be referred to [3-4] for detailed mathematics of DWT, which is beyond the scope of this paper.

A. *Wavelet-Based Feature Extractor*



cDi: ith level WT detail coefficients, i=1,2,…,n
Di: ith level reconstructed detail signal component, i=1,2,…,n
cAi: ith level WT approximation coefficients, i=1,2,…,n
An: nth level reconstructed approximation signal component

Fig. 1. The structure of a WT-based feature extractor

The structure of a WT-based feature extractor is shown in Fig. 1. A signal is inputted into two complementary filters and yields two sets of WT coefficients: detail coefficients cD1 and approximation coefficients cA1 for the 1st level. Note that the two filters, i.e. the high-pass filter and the low-pass filter are defined with some wavelets as the basis functions. Detail coefficients capture the low-scale (high-frequency) components of a signal, while approximation coefficients apprehend the high-scale (low-frequency) components. Then cA1 are inputted into the same filters again for further decomposition and generate the WT coefficients of the 2nd level: cD2 and cA2. This procedure is repeated until the last level n. The WT coefficients consist of n sets of detail coefficients cDi, i=1,2,…,n, and one set of approximation coefficients cAn, covering the entire spectrum of the signal. While each set corresponds to a specific frequency region, the levels of DWT are chosen based on specific requirements. In this research, we choose n=8, because of two reasons. One reason is that for the DLC maneuver, the 5th and 6th levels are the most critical levels to identify a driver's skill. Another reason is that given the sampling rate of 50Hz, the process becomes trivial after the 8th level, because the size of the time window is large enough to cover the entire time domain of data.

Fig. 1 also shows the signal reconstruction. The WT coefficients at each level go through an inverse WT and yield a reconstructed signal component of each level. Summing these signal components reconstructs the original signal. The signal reconstruction, which is only used for analysis, is not a part of the WT-based feature extractor.

In this research, we use the 4th order Daubechies wavelet, db4, because Daubechies wavelet family has a self-similarity property, which gives rise to a down-sampling technique for faster WT [3]. After a study, db4 meets our requirement.

For the data set under a sampling rate of 50Hz, a DWT process using db4 for feature extraction takes 6400–16000 real multiplications and additions. The DFT-based feature extractor in [1-2] conducts a 1024-point FFT for all runs, which requires 11264 complex multiplications and additions for each run. As feature extraction will be operated online, the number of operations results in a large difference in implementation. It is also worth mentioning that the DWT feature extraction is essentially a combination of several filtering processes, which can be implemented in real time, while DFT is not a real time operation in a general sense. In addition, when we only focus on certain levels for feature extraction, e.g. extracting discriminant features at the 5th and 6th levels, the computation cost can be further reduced.

B. *Feature in the Frequency Domain*

From [1-2], it is known that the second foment in the frequency spectrum of steering wheel angle signals is a discriminant feature to differentiate skillful drivers from typical drivers. Since the basis functions of wavelet analysis are not sines and cosines, it is interesting to see which levels cover the second foment, being the key to driving skill recognition. To show that, we select two runs completed by two drivers at different maneuvering speeds for illustration.

Run 493 is completed by subject 9996 at 30mph. Fig. 2 shows the amplitudes of the DFT coefficients of the steering wheel angle signal and the reconstructed signal components for the 5th–8th levels, i.e., D5, D6, D7, D8, and A8. The reconstructed component of each level represents a part of the original signal and corresponds to a scale. Conducting DFT on the reconstructed signal component of each level, we connect WT analysis to DFT analysis.

In Fig. 2, the blue line represents the DFT coefficients of the steering wheel angle signal, and clearly shows a second foment around 0.6Hz. It can be seen that the 6th level (black) whose pseudo-frequency is also around 0.6Hz, captures the second foment. The 5th level (red) whose pseudo-frequency is around 1Hz, reflects a high frequency part, where there is a third foment. The 7th and 8th levels (yellow, magenta, and cyan) cover a low frequency part, together contributing to the first foment ranging from 0Hz to 0.4Hz. The 3rd and 4th levels grasp higher frequency parts (above 1Hz). Compared to the 5th–8th levels, the amplitude of the DFT coefficients for these two levels is much smaller, indicating that they are not the key parts of the steering wheel angle signal. The 1st and 2nd levels are in the noise region with very small magnitudes of their DFT coefficients.

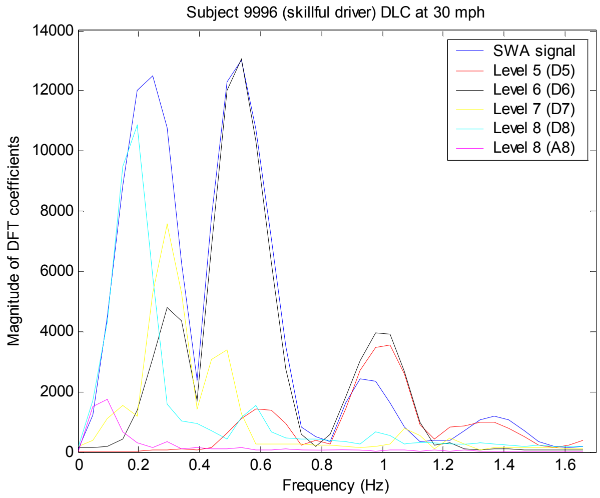


Fig. 2. DFT of reconstructed signal components (5th—8th level) for run 493

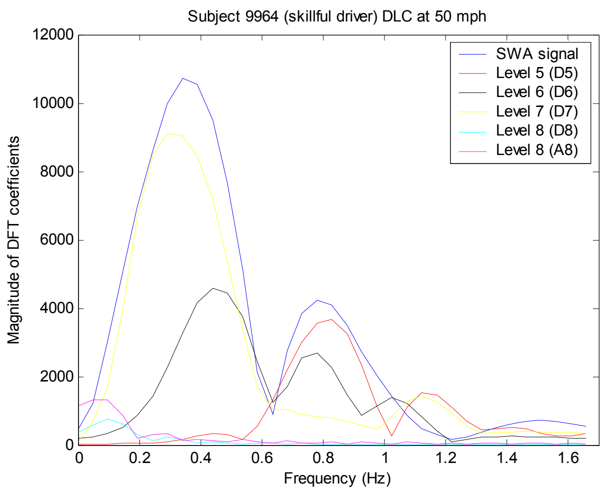


Fig. 3. DFT of reconstructed signal components (5th—8th level) for run 416

Next we investigate run 416 completed by subject 9964 at 50mph. Fig. 3 shows the amplitudes of the DFT coefficients of the original signal and the reconstructed components of the 5th—8th levels, i.e., D5, D6, D7, D8, and A8. The blue line represents the DFT coefficients of the original signal and shows a second foment around 0.8Hz. It can be seen that the 5th level (red) whose pseudo-frequency is around 1Hz captures the second foment. The 6th level (black) whose pseudo-frequency is around 0.6Hz also has a contribution to the second foment. The 7th level (yellow) whose pseudo-frequency is around 0.3Hz, captures the main part of the first foment. The two reconstructed signal components of the 8th level, i.e., D8 (cyan) and A8 (magenta), and the 6th level (black) also have contributions to the first foment, which ranges from 0Hz to 0.6Hz. Similar to run 493, the smaller amplitudes of the DFT coefficients indicates that the 3rd and 4th levels are not the key parts of the steering wheel angle signal, and the 1st and 2nd levels are in the noise region.

As a summary, we make the following conclusions. Given the speed from 20mph to 50mph and the sampling rate of 50Hz, the 5th and 6th levels have the most significant contributions to the second foment, which is the key to differentiate skillful drivers from typical drivers. The 7th and 8th levels have contributions to the first foment, which is the basic element for the completion of the DLC maneuver. Hence it is reasonable and more efficient to focus on the 5th and 6th levels for feature extraction rather than all levels. The evaluation results to be presented later also show that there is no performance loss for a recognizer using the 5th and 6th levels for feature extraction. To be comparable to the DFT-based feature extraction, which takes the first 30 points of the DFT coefficients normalized at the speed of 27mph, we will consider the 4th—8th levels for the comparison study, because these levels approximately cover to the same frequency region as the first 30 points of the normalized DFT coefficients. In fact including 1st—3rd levels into feature extraction does not improve the performance. It is worth mentioning that although the physical frequency of the second foment varies with the speed, there is no need for the WT-based feature extractor to normalize at a certain speed. This is because with WT, temporal information is explicitly displayed along the space axis at each level. A disadvantage of normalization is that it blurs the line between some typical drivers and skillful drivers for low speed runs.

C. *Feature in the Space Domain*

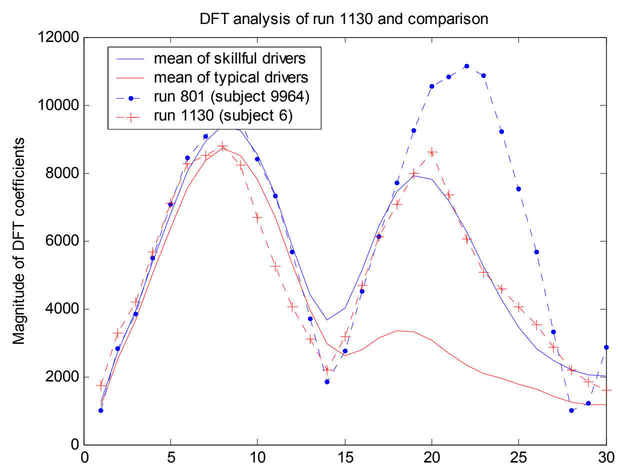


Fig. 4. Comparison of magnitudes of DFT coefficients

It has been observed that some typical drivers have a notable second foment in the frequency spectrum of some runs, especially when maneuvering at a low speed. It is hard for a classifier to recognize those runs as typical drivers only based on a feature in the frequency domain. To be specific, let us look at an example: run 1130 completed by subject 6 at 20mph under a dry surface condition. The survey shows that subject 6 is a typical driver. Taking 1024-point DFT on the steering wheel angle, we plot the magnitude of the DFT coefficients for the first 30 points in Fig. 4 (red dotted). For comparison, we choose run 801 completed by subject 9964, who is a skillful driver, at 20mph under the same scenario. The frequency spectrum of run 801 is also plotted in Fig. 4 (blue dotted). For better illustration, the means of DFT magnitudes for all skillful (blue) and typical drivers (red) are also shown in Fig. 4. It shows that at a low speed subject 6 has a notable second foment in the frequency spectrum, which is similar to subject 9964. Meanwhile looking at the means of DFT magnitudes, we notice that run 1130 will be recognized as a skillful driver's behavior instead of a typical drive's behavior if we use the DFT feature extraction.

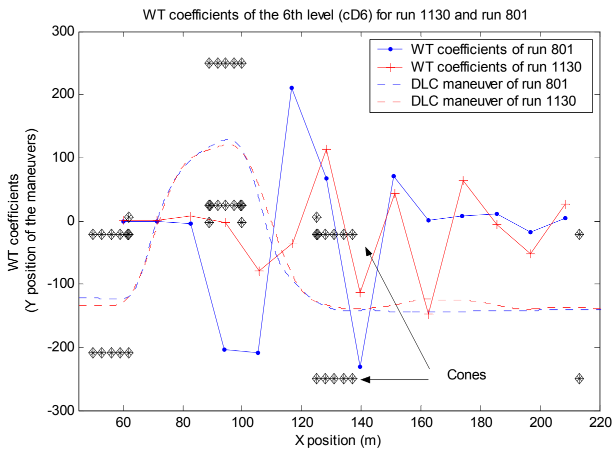


Fig. 5. cD6 and maneuvers

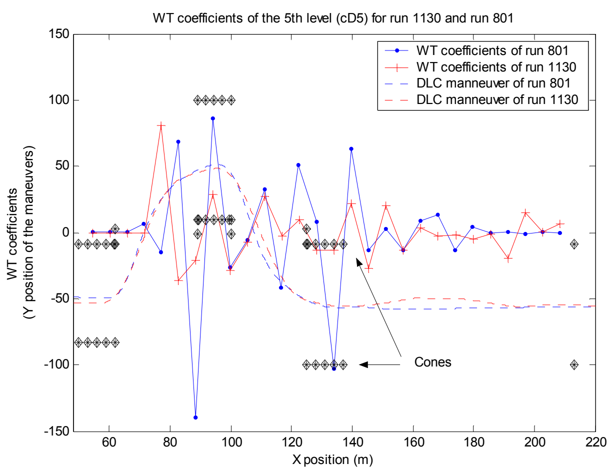


Fig. 6. cD5 and maneuvers

Fig. 5 and Fig. 6 show the WT coefficients of both runs at the 6th and the 5th level respectively. For better illustration, the maneuvers of both runs are also plotted (dotted) along with the cones. From Fig. 5, we observe that the magnitude of the WT coefficients for run 801 is larger than that for run 1130 in the space region (X position) from 60 meter to 130 meter, which corresponds to the lane change operation in the DLC maneuver. Moreover we notice that for run 801 large coefficients appear in an early stage of the DLC operation (80 to 130 meter), while large coefficients occur much later in the space (after 130 meter) for run 1130. The explanation is that skillful drivers are more proactive than typical drivers. Skillful drivers tend to look into the road further and observe the surrounding environment more actively so as to make a quicker but more precise decision. Typical drivers are less capable of observing the environment and tend to have corrections to the steering wheel angle in a late stage of the operation to compensate for the error. In Fig. 6 a similar characteristic can be observed. In this case the 6th level plays a more important role in the second foment than the 5th level at speed 20 mph. This fact can also be verified by noticing the magnitudes of WT coefficients of both levels.

D. Feature Extraction

To avoid redundancy and reduce implementation cost, we use a technique to take weighted averages on the magnitude and the X position of the WT coefficients for each level before inputting them into a classifier. Fig. 7 plots the 6th level WT coefficients of run 493. Consider the region enclosed by the x-axis and the curve representing the magnitude of the WT coefficients. To equally emphasize both frequency and space, we calculate the "center" of this region. Assume that the area is defined on a closed interval $x \in [a,b]$, and use $f(x)$ to describe the curve. The formula to calculate the area center $(\bar{x}, \bar{y})$ is

$$\bar{x} = \frac{1}{A}\int_a^b xf(x)dx, \quad \bar{y} = \frac{1}{A}\int_a^b \frac{1}{2} f^2(x)dx \qquad (1)$$

where A is the area of the region defined by $A = \int_a^b f(x)dx$.

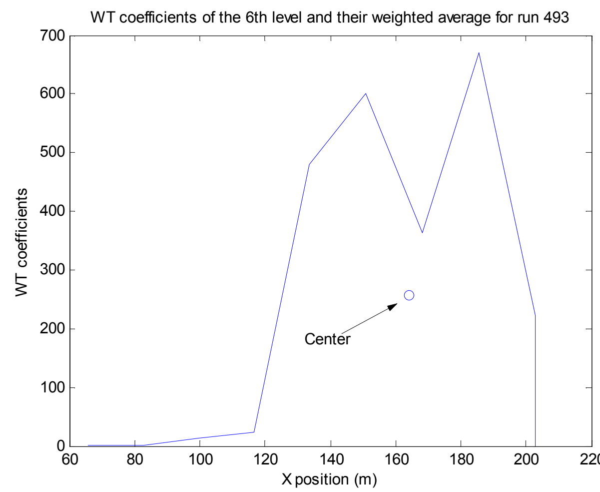


Fig. 7. WT coefficients (magnitude) of the 6th level and the weighted average of WT coefficients (magnitude) for run 493

Use an n-dimension vector $x = [x_1, x_2, \dots x_n]$ to define the X position and another vector $y = [y_1, y_2, \dots y_n]$ for the magnitude. We rewrite (1) into a discrete fashion as

$$\bar{x} = \frac{1}{A}\sum_{i=2}^{n} x_i y_i (x_{i+1} - x_i), \quad \bar{y} = \frac{1}{A}\sum_{i=2}^{n} \frac{1}{2} y_i^2 (x_{i+1} - x_i) \quad (2)$$

where $A = \sum_{i=2}^{n} y_i (x_{i+1} - x_i)$. With this technique, a pair of coordinates is used to characterize the discriminant feature for one run at each level. We plot the discriminant feature on a two-dimensional plane with the horizontal axis to indicate the averaged position $\bar{x}$ and the vertical axis to indicate the averaged magnitude $\bar{y}$. Based on the previous discussions, it is predicted that the features of skillful drivers tend to be in the upper left corner, and the features of typical drivers tend to be in the lower right corner. Fig. 8 shows the discriminant features for all runs at the 6th level. In Fig. 8, visually we can draw such a line to divide these runs into two groups of skillful and typical drivers respectively. Recall run 1130, which cannot be recognized as a typical driver's behavior with the DFT-based feature extractor. Fig. 8 shows the discriminant features of run 1130 and run 801 generated by the WT-based extractor against the collective features of the 6th level for all runs. It can be seen that we can successfully differentiate run 1130 from skillful drivers' runs.

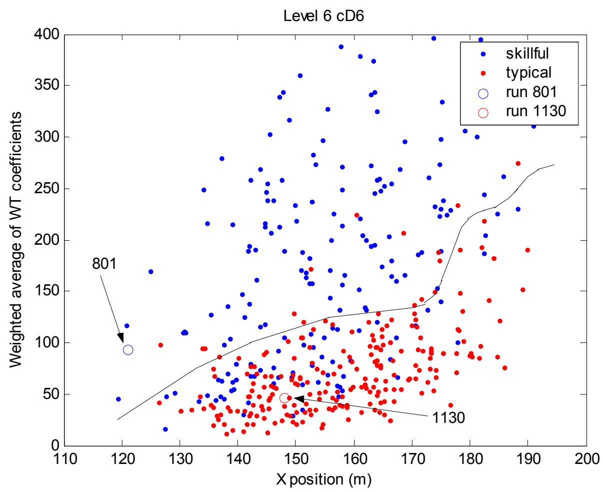


Fig. 8. Collective discriminant features for the 6th level

E. RBN-Based Classifier

The function of a classifier is to identify drivers with their skill levels based on the discriminant features from a feature extractor. Neural networks have been extensively used for classification such as the Feed-Forward Neural Network (FNN) used in [1]. Radial Basis Networks (RBNs) are alternatives to FNNs. Similar to FNNs, RBNs have two layers: a hidden layer of n radial basis neurons and an output layer of a linear neuron. RBNs use radial basis functions in the neurons of the hidden layer rather than the sigmoidal or other S-shaped functions as in FNNs. A typical radial basis function is the Gaussian function, which is given by

$$f_i(x,c_i,r_i) = \exp\left(-\left(\|x-c_i\|/r_i\right)^2\right) \quad , \quad i \in \{1,2,\ldots,n\} \qquad (3)$$

where $x=[x_1, x_2,\ldots, x_m]^T$ is the input, c_i is the center of the function, and r_i is the radius that determines the shape of the function. The output neuron is formed by a weighted sum of the outputs of the radial basis neurons and a unity bias. Two properties of RBNs: linear parameterization and locality [8] result in a simple update law, which is operated easily and much faster than the back propagation algorithm.

III. Comparison Study

The WT-based feature extraction is compared with the DFT-based feature extraction. Three classifiers: FNN-based, RBN-based, and SVM-based, are integrated with both extractors. A set of discriminant feature vectors is used as training data to train the classifiers. Another set is used as testing data to be inputted into the classifiers for driving skill recognition. A ten-fold cross-validation test as explained in [1] is conducted to evaluate the recognition performance.

The correct recognition rate (CRR) is defined by

$$\frac{\text{Number of correctly recognized runs}}{\text{Number of total runs}}.$$

A. Comparison over All Subjects

The average CRRs for six recognizers are summarized in Table 1. In general the WT-based extractor outperforms the DFT-based extractor in terms of CRRs. The WT-based extractor increases the overall CRRs by 4% with the FNN classifier, 4% with the RBN classifier, and 6% with the SVM classifier. However, with the RBN classifier, the WT-based extractor has a worse recognition of skillful drivers. This is due to the choice of the spread of the RBN. It has been observed that the smaller the spread, the higher the CRR of skillful drivers and vice versa. The reason is because the frequency spectrum of a typical driver is more stationary than that of a skillful driver such that a more local RBN with a smaller spread is more capable of recognizing skillful drivers. We can see that the spread is not balanced for the WT-based extractor, leading to a high CRR for typical drivers and a low CRR for skillful drivers.

TABLE 1

PERFORMANCE COMPARISON OF DFT-BASED & WT-BASED EXTRACTORS

Classifier	FNN Classifier		RBN Classifier		SVM Classifier	
Extractor	DFT	WT	DFT	WT	DFT	WT
CRR for Skillful (%)	68	72	73	69	76	82
CRR for Typical (%)	78	81	84	93	82	89
Overall CRR (%)	73	77	79	83	80	86

B. Impact of Subject 357

A further investigation on individual drivers reveals that subject 357 causes misrecognition especially for low speed runs. In [1] we have concluded that the frequency spectrum of the steering wheel angle signals of subject 357 is closer to typical drivers than to expert drivers in terms of mean DFT coefficients. Applying wavelet analysis, we see that subject 357 still causes misrecognition, because most of his runs are close to the boundary that divides the two categories.

TABLE 2

PERFORMANCE COMPARISON OF RECOGNITION WITH AND W/O 357

Recognizer	DFT-FNN		DFT-RBN		DFT-SVM	
Subject 357	w	w/o	w	w/o	w	w/o
CRR for Skillful (%)	68	75	73	82	76	84
CRR for Typical (%)	78	89	84	92	82	90
Overall CRR (%)	73	83	79	88	80	88
Recognizer	WT-FNN		WT-RBN		WT-SVM	
Subject 357	w	w/o	w	w/o	w	w/o
CRR for Skillful (%)	72	76	69	81	82	88
CRR for Typical (%)	81	90	93	96	89	93
Overall CRR (%)	77	85	83	90	86	91

The comparison results of the two cases, i.e., with and without subject 357, for the six recognizers are summarized in Table 2. The DFT-FNN, DFT-RBN, and DFT-SVM recognizers increase the overall CRR by 10%, 9%, and 8%

respectively without subject 357. The WT-FNN, WT-RBN, and WT-SVM recognizers increase the overall CRR by 8%, 7%, and 5% respectively without subject 357.

C. Study of 5TH-and-6TH-Level Extractor

As addressed in Section 2, among all WT levels, the 5th and 6th levels are the most significant to driving skill recognition. It is beneficial using less resource (e.g., less memory and throughput of CPU due to less data to be handled) to extract same discriminant features without loss of quality. In this subsection, we study a WT-based feature extractor that only uses the WT coefficients of the 5th and 6th levels to construct the discriminant feature and compare it with the 4th-to-8th-level WT-based extractor.

TABLE 3
PERFORMANCE COMPARISON OF THE 5TH-AND-6TH-LEVEL WT-BASED EXTRACTOR AND THE 4TH-TO-8TH-LEVEL WT-BASED EXTRACTOR

Extractor	5th-and-6th-level			4th-to-8th-level		
Classifier	FNN	RBN	SVM	FNN	RBN	SVM
CRR for Skillful (%)	66	68	79	72	69	82
CRR for Typical (%)	84	95	88	81	93	89
Overall CRR (%)	76	83	84	77	83	86

The average CRRs for the two WT-based extractors with three classifiers are summarized in Table 3 to assess the effectiveness of the 5th-and-6th-level WT-based extractors. In terms of CRRs, there is no much difference between the two feature extractors. We conclude that for all three classifiers the 5th-and-6th-level WT-based extractor maintains a similar performance to the 4th-to-8th-level extractor. However the 5th-and-6th-level WT-based extractor uses less resource.

We also compare the 5th-and-6th-level WT-based feature extractor and the 4th-to-8th-level feature extractor for the case without subject 357 in order to evaluate the impact of subject 357 to the 5th-and-6th-level extractor. The average CRRs for the two WT-based extractors with three classifiers are summarized in Table 4. In terms of CRRs, there is no much difference between the two feature extractors.

TABLE 4
PERFORMANCE COMPARISON OF THE 5TH-AND-6TH-LEVEL WT-BASED EXTRACTOR AND THE 4TH-TO-8TH-LEVEL WT-BASED EXTRACTOR W/O 357

Extractor	5th-and-6th-level			4th-to-8th-level		
Classifier	FNN	RBN	SVM	FNN	RBN	SVM
CRR for Skillful (%)	74	79	88	76	81	88
CRR for Typical (%)	91	96	91	90	96	93
Overall CRR (%)	85	90	90	85	90	91

A. Comparison Study of Three Classifiers

The three classifiers are also compared to investigate their effectiveness. The average CRRs for the six recognizers are collected in Table 5. It shows that the SVM-based classifier outperforms the FNN-based classifier by 7% and the RBN-based classifier by 1% with the DFT-based extractor and by 5% and 3% for each with the WT-based extractor. The best performance of the SVM-based classifier suggests that the extracted discriminant feature may have a similar distribution over all of the drivers. The RBN-based classifier outperforms the FNN-based classifier due to the advantage of RBNs in locality over FNNs. Also referring to Table 2 for the impact of subject 357, we see that all algorithms have difficulties recognizing subject 357. It implies that a feature extractor is more fundamental to differentiate drivers' skills. However the SVM-based classifier is more robust to subject 357 than the RBN-based and FFN-based classifiers. This observation suggests that the extracted discriminant feature of subject 357 still follows the assumption of a similar distribution, although it is close to the boundary.

TABLE 5
PERFORMANCE COMPARISON OF CLASSIFIERS

Extractor	DFT-Based Extractor			WT-Based Extractor		
Classifier	FNN	RBN	SVM	FNN	RBN	SVM
CRR for Skillful (%)	68	73	76	72	69	82
CRR for Typical (%)	78	84	82	81	93	89
Overall CRR (%)	73	79	80	77	83	86

IV. CONCLUSIONS

A WT-based feature extraction scheme and a new RBN-based classifier are proposed for driving skill recognition. A comparison study is conducted for three feature extractors: DFT-based, 4th-to-8th-level WT-based, 5th-and-6th-level WT-based, and three classifiers: FNN-based, RBN-based, SVM-based. We conclude that the WT-based feature extractors outperform the DFT-based extractor and the SVM-based classifier has the best performance among the classifiers. Future work aims at further validation with real driving data to close the gap between the simulator and the real world.

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