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Misclassification Tolerable Learning for Robust Pedestrian Orientation Classification

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***Abstract*—In this paper, we propose a multiclass classifier training method which reduces "fatal" misclassifications by cost-relaxation of "tolerable" misclassifications in one-against-all classifiers training, named misclassification tolerable learning. In a binary classifier in the one-against-all classifiers, we introduce a new class group "conceptually similar classes," whose class labels are similar to the positive class. In the case of pedestrian orientation classification, the conceptually similar classes are defined as neighboring orientations to the positive orientation. We consider the misclassification of the conceptually similar classes to the positive class as tolerable misclassification. By relaxing the cost of the tolerable misclassifications, our proposed classification method reduces fatal misclassifications of non-similar classes. We evaluated the cost-relaxation effectiveness on several public datasets and confirmed that the proposed method outperforms the normal SVM on all of the datasets in the soft criterion by achieving 78.63% recognition rate on PDC Dataset.**

I. Introduction

Technologies related to Advanced Driver Assistance Systems (ADAS) have been actively developed in recent years. The main focus of the technologies is to reduce the risk of traffic accidents. Since a huge number of pedestrians are killed in traffic accidents, reducing traffic accidents involving pedestrians is one of the most important problems. To avoid such accidents, various sensors are installed in state-of-the-art vehicles. Among the sensors, recently, in-vehicle camera is considered as an useful sensor, and many technologies using an in-vehicle camera for ADAS have been developed. Detecting pedestrians from it is one of the most active topics and many papers are published. For more advanced driver assistance, not only detecting pedestrians, but also predicting their behavior from an in-vehicle camera, especially, predicting the walking direction of a pedestrian is required.

To predict walking direction or behavior of a pedestrian, his/her trajectory is one important key. However, it is difficult to obtain trajectories of pedestrians who are standing still. The orientation of a pedestrian is also an important key and pedestrian orientation classification is also actively developed. If we can classify his/her orientation from an in-vehicle camera, the information should be a valuable prior to predict his/her walking direction or behavior.

In many researches, pedestrian orientations are divided into several classes, and the problem is formulated as a multiclass classification problem [1]–[8]. Most of these methods classify pedestrian orientations into four or eight classes (e.g. S (south), SW (south west), W (west), ..., SE (south east), as shown in Fig. 1) by using a multiclass classifier, such as a combination of Support Vector Machines (SVMs). If a classification system classified the orientation of a pedestrian in the correct orientation class, the classification is judged as a success, and vice versa.

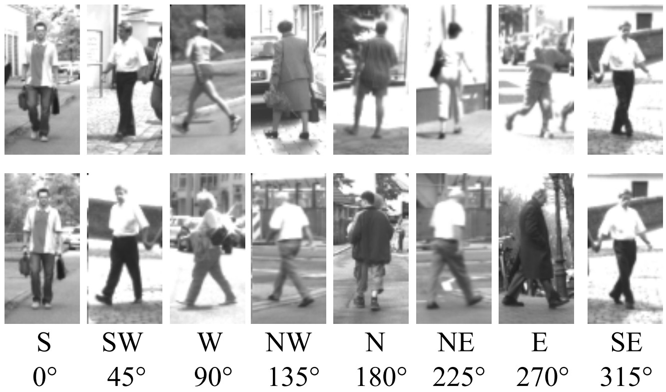


Fig. 1. Images sampled from PDC dataset introduced by Tao et al. [6]. The pedestrian orientation classification problem is usually formulated as a multiclass classification problem by dividing its orientation into several discrete classes.

In the orientation classification problem for pedestrian behavior prediction, if the system classified the orientation as the opposite orientation to the truth, it is considered as a fatal misclassification (Fig. 2(iii)). However, if the system classified the orientation as neighboring orientations of the truth (Fig. 2(iv)), it is not necessarily fatal, since in some cases, the misclassification is tolerable because the neighboring orientations are conceptually similar to the truth.

To generalize this, considering actual applications, although misclassification to non-similar classes makes a fatal error, misclassification to conceptually similar classes does not make a fatal error for the application.

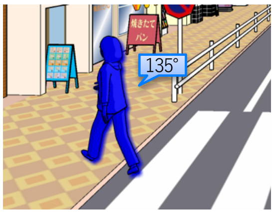
Existing multiclass classifiers do not consider such conceptual similarity of classes, and they are trained under the premise that the misclassification penalty should be the same for all classes, regardless of their conceptual similarity.

Our contributions are summarized as follows:

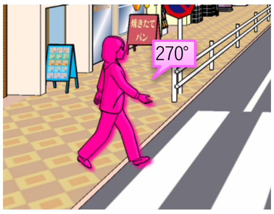
1) We introduce concepts of two class groups; one is conceptually similar classes which consists of classes whose class labels are similar to the positive class, and the other is non-similar classes which consists of classes

(i) Observation

(ii) Truth



(iii) Fatal misclassification



(iv) Tolerable misclassification

Fig. 2. Pedestrian orientation classification for behavior prediction. (i) Observation image. (ii) Truth of orientation classification. (iii) Misclassification to the opposite orientation to the truth. In this case, the classification result will lead to fatal error for behavior prediction. (iv) Misclassification to a neighboring orientation of the truth. In this case, the classification result can be tolerable for behavior prediction.

whose class labels are not similar to the positive class. We consider the misclassification of the conceptually similar classes to the positive class can be tolerable for the application.

2) We propose misclassification tolerable learning, which is a multiclass classifier training with cost-relaxation of tolerable misclassifications. Tolerating misclassifications of the conceptually similar classes to the positive class by cost-relaxation and tuning the classifier to separate the positive class and the non-similar classes, our proposed method can reduce fatal misclassifications and increase the entire classification accuracy.
3) For evaluation, we apply this classifier to the pedestrian orientation classification problem, and show that it can actually reduce fatal misclassifications.

The rest of the paper is organized as follows: Section II summarizes previous work on pedestrian orientation classification and multiclass classifiers. In Section III, details of our proposed method are introduced. Experimental results are reported in Section IV. Finally, we conclude this paper in Section V.

II. Related Work

A. Pedestrian Orientation Classification

Existing researches on pedestrian orientation classification from an image can be mainly divided into two approaches. One is an approach using a pedestrian detector for each orientation [1], [2], and the other is an approach that applies a pedestrian orientation classifier to the detected pedestrians. In this paper, we assume that pedestrian bounding boxes are given, thus we follow the latter approach.

Generally, many researches on pedestrian orientation classification focus on developing features or modifying classification methods.

Gandhi et al. [9] proposed an orientation estimation method using Histograms of Oriented Gradients (HOG) feature and Support Vector Machine (SVM). Tao et al. [6] proposed part-based features to accurately classify pedestrian orientations with a Random Decision Forest. Shimizu et al. [10] proposed an orientation classification method which combines sixteen orientation classifier outputs by a decision function.

As an additional sensing device, depth sensor is usually used. Liu et al. [5] proposed an orientation classification method using an RGB-D sensor. Shinmura et al. [7], [8] introduced a method using an RGB-ToF camera. This method uses the depth information for background removal to reduce background noise and use the depth information for feature weighting to enhance the pedestrian features. These methods also make use of a multiclass classifier to classify pedestrian orientations.

B. Support Vector Machine for Multiclass Classification

Support Vector Machine (SVM) is one of the well known and practical binary classifiers, which is known for its high classification performance. A multiclass classifier can be constructed by combining multiple binary classifiers, usually SVMs.

There are several approaches to combine binary classifiers to construct a multiclass classifier [11]–[14]. Among them, two common combination methods are mainly used; one is the one-against-one scheme [12], and the other is the one-against-all scheme [14]. For classes $c_1, c_2, \ldots, c_K$, the one-against-one scheme combines ${}_K\mathrm{C}_2$ binary classifiers of all combinations of c_i and c_j. On the other hand, the one-against-all scheme combines K classifiers; Each classifier is a binary classifier where class c_i is the positive class and the other classes $\{c_1, \ldots, c_K\}_{\backslash c_i}$ are negatives. Here, $\{c_1, \ldots, c_K\}_{\backslash c_i}$ denotes the classes except class c_i. For the one-against-all scheme, all classes except c_i are equivalently considered as negatives.

The one-against-all scheme can obtain higher accuracy in case of small number of classes [15]. Since our problem usually requires a small number of classes, as introduced in section I, we follow the one-against-all approach.

III. Misclassification Tolerable Learning

A. Introduction of Conceptually Similar Classes

In the original one-against-all scheme, each binary classifier is trained to classify two classes; a positive class c_i and the others $\{c_1, c_2, \ldots, c_K\}_{\backslash c_i}$. It handles "the others" as a single negative class. On the other hand, our proposed method divides "the others" into two negative class groups; *conceptually similar classes* and *non-similar classes*. Thus, in our method, each binary classifier handles a positive class, conceptually similar classes, and non-similar classes. Actually, both the conceptually similar classes and the non-similar classes are

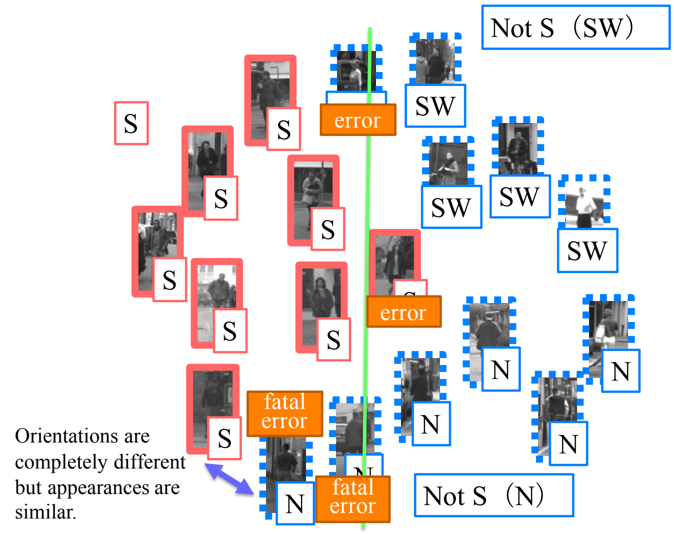


Fig. 3. Normal binary classifier for classes S and Not S (classes SW and N in the figure). Some images in classes S and N appear similarly. To minimize misclassification, we can draw a classification hyper plane as shown in the figure. In this example, there are four misclassifications including two fatal ones.

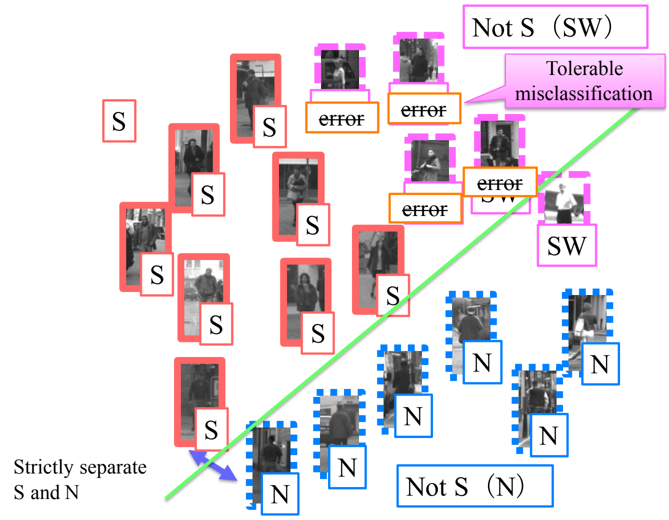


Fig. 4. Proposed binary classifier for class S and classes Not S. In the proposed method, class Not S is divided into two class groups; Conceptually Similar Classes and Non-Similar Classes. Misclassifications of Conceptually Similar Classes are tolerated. In this example, misclassification of class SW to S is tolerated, so we can draw a classification hyperplane as shown in the figure. Four misclassifications are tolerated.

negatives, but the proposed binary classifiers tolerate misclassifications of the conceptually similar classes to the positive class. We consider such misclassification of the conceptually similar classes as "tolerable misclassification".

Here, we define the *conceptually similar classes* as a class group which consists of classes whose class labels are similar to the positive class label. For this discussion, class label similarity must be defined. In this paper, we focus on a problem that class label similarity can be defined, such as pedestrian orientation classification.

B. Class Label Similarity in Pedestrian Orientation Classification

Pedestrian orientation classification is a multiclass classification problem of divided orientations whose class labels are usually four or eight orientations. Each class c_i is described as a representative orientation degree $d(c_i)$, like S (0°), SW (45°), ..., SE (315°). Therefore, we can define the class label similarity by using the difference of the orientations in degrees. Because orientation degree is cyclic, using a cosine function, we define the similarity of classes c_i and c_j as

$$s(c_i, c_j) = \cos(|d(c_i) - d(c_j)|). \tag{1}$$

In this definition, we can say that classes S (0°) and SW (45°) are more similar than classes S (0°) and N (180°). Generally, the neighboring orientation classes are similar in this definition. Here, we define conceptually similar classes (csc) of class c_i and non-similar classes (nsc) of class c_i as

$$\mathrm{csc}(c_i) = \{c_j | \forall j, s(c_i, c_j) \geq T, c_i \neq c_j\}, \tag{2}$$

$$\mathrm{nsc}(c_i) = \{c_j\}_{\backslash c_i} - \mathrm{csc}(c_i), \tag{3}$$

where $\mathrm{csc}(c_i)$ is the conceptually similar classes of class c_i and $\mathrm{nsc}(c_i)$ is the non-similar classes of class c_i respectively, and T denotes a thresholding parameter. In this paper, we set $T = \sqrt{2}/2$, where the maximum difference among the orientations in degree of conceptually similar classes is 45°, therefore, neighboring orientations in classification of eight orientations are considered as the conceptually similar classes.

C. Cost-Relaxation in the Classifier Training

We introduce a binary classifier which relaxes the misclassification cost of the conceptually similar classes to the positive class and tunes for separating the positive class and the non-similar classes. It reduces fatal misclassifications while tolerating misclassifications of the conceptually similar classes to the positive class. To realize this, we modify the soft-margin SVM optimization function in Eq. (4) to Eq. (8).

Let $\mathbf{x}_i$ be a training sample, y_i its binary class label, $\mathbf{w}$ and b the classification hyperplane parameters, C the soft margin parameter, and ξ_i the slack variable, the SVM optimization function of a binary classifier (class c_p or not) can be written as

$$\operatorname*{argmin}_{\mathbf{w},b,\boldsymbol{\xi}} \frac{1}{2}||\mathbf{w}||^2 + C\sum_{i=1}^{N}\xi_i \tag{4}$$

subject to

$$\begin{cases} y_i(\mathbf{w}^T\phi(\mathbf{x}_i) + b) \geq 1 - \xi_i, \\ \xi_i \geq 0, \end{cases} \tag{5}$$

where

$$y_i = \begin{cases} 1, & \text{if } \mathbf{x}_i \in c_p \\ -1, & \text{if otherwise.} \end{cases} \tag{6}$$

Here, we introduce cost-relaxation parameters

$$s_i = \begin{cases} s, & \text{if } \mathbf{x}_i \in c, c \in \mathrm{csc}(c_p), \\ 1, & \text{otherwise,} \end{cases} \tag{7}$$

where s (≤ 1) denotes a cost-relaxation weight parameter. Using these parameters, our proposed SVM optimization function can be written as

$$\underset{\mathbf{w},b,\boldsymbol{\xi}}{\operatorname{argmin}} \frac{1}{2}||\mathbf{w}||^2 + C\sum_{i=1}^{N} s_i \xi_i \tag{8}$$

subject to

$$\begin{cases} y_i(\mathbf{w}^T\phi(\mathbf{x}_i) + b) \geq 1 - \xi_i, \\ \xi_i \geq 0. \end{cases} \tag{9}$$

This is a variation of the weighted SVM [16] which is a generalization of the standard SVM. The difference from the general weighted SVM is that the method restricts the weights by the label similarities.

As same as the weighted SVM, the dual problem of Eq. (8) can be written as

$$\tilde{L}(\boldsymbol{\lambda}) = \sum_{i=1}^{N} \lambda_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \lambda_i \lambda_j y_i y_j k(\mathbf{x}_i, \mathbf{x}_j), \tag{10}$$

subject to

$$\begin{cases} 0 \leq \lambda_i \leq s_i C, \\ \sum_{i=1}^{N} \lambda_i y_i = 0, \end{cases} \tag{11}$$

where $\boldsymbol{\lambda} = \{\lambda_i\}$ denotes the Lagrange variables, and $k(\mathbf{x}_i, \mathbf{x}_j)$ is a kernel function. By optimizing the function $\tilde{L}(\boldsymbol{\lambda})$, we can calculate the classification hyperplane parameters $\mathbf{w}$ and b.

D. *Classifier Characteristics of the Proposed Method*

Here, we discuss the effect of cost-relaxation of tolerable misclassification in the one-against-all classifier training. We show an example of pedestrian orientation classification by standard SVM and the proposed method in Fig. 3 and Fig. 4, respectively.

In the example, some of image features in classes S and N are similar, although there is a large difference between their class labels. The classifier is trained to classify class N from class S, and class SW from class S, simultaneously. Therefore, by minimizing the misclassifications, the classification hyperplane in Fig. 3 is drawn. In this case, we obtain four misclassifications including two fatal ones.

On the other hand, in the proposed method, we divide the negative class {SW, N, ...} into the conceptually similar classes {SW, ...} and the non-similar classes {N, ...} as shown in Fig. 4. By giving a smaller cost-relaxation weight parameter to the training samples in the conceptually similar classes, the classifier tolerates the misclassification of the conceptually similar classes to the positive class, and is tuned to separate the positive class S and the non-similar classes {N, ...}. As a result, the classification hyperplane in Fig. 4 is drawn. In this case, we obtain the same number of misclassifications, but they are tolerable for the application.

S	SW	W	NW	N	NE	E	SE
0°	45°	90°	135°	180°	225°	270°	315°

Fig. 5. Images sampled from TUD dataset introduced by Andriluka et al. [17]. To make the condition same as PDC dataset, we cropped pedestrians in the same aspect ratio and converted them to gray-scale images.

IV. EVALUATION

To evaluate the classification performance of the proposed method, we compared several methods with two public datasets.

A. *Datasets*

1) TUD Multiple View Pedestrian Dataset: This dataset (TUD dataset) is provided by Andriluka et al. [17]. This dataset is composed of 5,183 bounding boxes in color images with annotations of eight orientations. It includes 4,935 bounding boxes for training and 248 bounding boxes for testing. Annotations of the dataset consists of skeletons, orientations, and bounding boxes. We crop pedestrian images using the provided bounding boxes. As the images in TUD dataset are color, in order to make the same condition with the following PDC dataset, we apply color to gray conversion. Some examples of images in the dataset are shown in Fig. 5.

2) Pedestrian Direction Classification Dataset: This dataset (PDC dataset) is provided by Tao et al. [6]. This dataset is based on the Daimler Mono Pedestrian Detection Benchmark Dataset [18], which is commonly used as a pedestrian detection benchmark. Pedestrian images in the dataset are already cropped and annotations of pedestrian orientation are also already manually annotated on the dataset. The dataset is composed of 11,562 gray pedestrian images with annotations of eight orientations. Some examples of images in the dataset are shown in Fig. 1.

B. *Compared Methods*

To evaluate the effectiveness of the proposed method, we compare SVM classifiers with/without cost-relaxation for conceptually similar classes.

- SVM (Standard): Traditional Support Vector Machine.
- SVM (Cost-relaxation): Proposed method.

In this evaluation, we used one-against-all scheme for multi-class classification.

TABLE I
RECOGNITION ACCURACY COMPARISON ON TUD DATASET

	Classification criteria (%)	
	Strict	Soft
SVM (Normal)	47.58	75.40
SVM (Cost-relaxation)	50.40	78.63

TABLE II
CONFUSION MATRIX OF THE PROPOSED METHOD ON TUD DATASET

	S	SW	W	NW	N	NE	E	SE
S	0.41	0.08	0.08	0.00	0.26	0.03	0.05	0.10
SW	0.11	0.51	0.24	0.05	0.08	0.00	0.00	0.00
W	0.00	0.00	0.78	0.22	0.00	0.00	0.00	0.00
NW	0.11	0.08	0.21	0.42	0.18	0.00	0.00	0.00
N	0.17	0.05	0.00	0.05	0.61	0.02	0.02	0.07
NE	0.05	0.21	0.00	0.00	0.11	0.21	0.26	0.16
E	0.00	0.00	0.00	0.00	0.00	0.15	0.77	0.08
SE	0.12	0.00	0.00	0.08	0.04	0.04	0.44	0.28

TABLE III
CONFUSION MATRIX OF THE CONVENTIONAL METHOD ON TUD DATASET

	S	SW	W	NW	N	NE	E	SE
S	0.26	0.13	0.03	0.00	0.38	0.00	0.03	0.18
SW	0.14	0.54	0.16	0.08	0.08	0.00	0.00	0.00
W	0.00	0.09	0.57	0.30	0.00	0.00	0.00	0.04
NW	0.16	0.11	0.13	0.42	0.18	0.00	0.00	0.00
N	0.20	0.05	0.00	0.05	0.61	0.02	0.02	0.05
NE	0.11	0.16	0.00	0.00	0.16	0.37	0.16	0.05
E	0.00	0.08	0.00	0.00	0.00	0.19	0.65	0.08
SE	0.08	0.00	0.00	0.12	0.04	0.08	0.28	0.40

TABLE IV
RECOGNITION ACCURACY COMPARISON ON PDC DATASET

	Classification criteria (%)	
	Strict	Soft
SVM (Normal)	83.52	97.20
SVM (Cost-relaxation)	81.66	97.76

TABLE V
CONFUSION MATRIX OF THE PROPOSED METHOD ON PDC DATASET

	S	SW	W	NW	N	NE	E	SE
S	0.82	0.08	0.01	0.00	0.03	0.00	0.00	0.06
SW	0.08	0.66	0.23	0.00	0.01	0.01	0.00	0.00
W	0.01	0.13	0.79	0.05	0.01	0.00	0.01	0.00
NW	0.00	0.00	0.15	0.68	0.16	0.00	0.00	0.00
N	0.01	0.00	0.00	0.04	0.91	0.04	0.00	0.00
NE	0.00	0.00	0.00	0.00	0.20	0.62	0.16	0.01
E	0.00	0.00	0.01	0.00	0.00	0.04	0.90	0.05
SE	0.11	0.00	0.00	0.01	0.02	0.01	0.19	0.66

TABLE VI
CONFUSION MATRIX OF THE CONVENTIONAL METHOD ON PDC DATASET

	S	SW	W	NW	N	NE	E	SE
S	0.90	0.03	0.01	0.00	0.03	0.00	0.01	0.03
SW	0.16	0.48	0.31	0.01	0.02	0.01	0.01	0.00
W	0.01	0.09	0.83	0.04	0.01	0.00	0.01	0.00
NW	0.01	0.00	0.12	0.67	0.18	0.00	0.01	0.00
N	0.01	0.00	0.00	0.02	0.93	0.03	0.00	0.00
NE	0.00	0.00	0.00	0.00	0.20	0.64	0.14	0.00
E	0.00	0.00	0.01	0.00	0.01	0.04	0.91	0.03
SE	0.15	0.00	0.00	0.00	0.04	0.01	0.19	0.61

For both classifiers, we used Radial Basis Function (RBF) for the kernel function. We tuned the soft-margin parameter and a parameter of RBF kernel by cross validation suitable for the standard SVM. We set the cost-relaxation parameter $s = 0$ empirically for the following evaluations.

C. Feature

Various features to describe a pedestrian image have been proposed. Since we do not care about the features in the proposed method, we simply use Histograms of Oriented Gradients (HOG) feature proposed by Dalal et al. [19], which is the most popular feature for pedestrian description.

D. Evaluation Criteria

In the proposed method, since we aim to reduce fatal misclassifications by cost-relaxation of tolerable misclassifications, as evaluation criteria, we introduce not only the strict eight-orientations classification accuracy but also a "soft" classification criterion, which tolerates the misclassifications to the neighboring orientation classes. Thus, in the "soft" criterion, we do not count the misclassifications to the neighboring orientation classes as false.

The evaluation criteria are summarized as:

- Strict criterion: Strictly evaluates the misclassifications.
- Soft criterion: Tolerates the misclassifications to the neighboring orientation classes.

E. Single Dataset Evaluation Results

1) TUD dataset: First, we evaluated the methods on TUD dataset. The classification results are shown in TABLE I. We can see that the proposed method achieved higher classification accuracies in both criteria.

The confusion matrices are shown in TABLES II and III. In these tables, we can see that the proposed method reduced "fatal" misclassifications.

2) PDC dataset: Then, we evaluated the methods on PDC dataset. Since the dataset is not divided into training/testing samples, we performed five-fold cross-validation for the evaluation on this dataset.

The classification results are shown in TABLE IV. We can see that the proposed method achieved lower classification accuracy in strict criterion but higher classification accuracy in "soft" criterion.

The confusion matrices are shown in TABLES V and VI. In these tables, we can also see that the proposed method increased tolerable misclassifications but reduced "fatal" misclassifications.

F. Cross-Dataset Evaluation Results

To evaluate the generalization performance, we performed a cross-dataset evaluation. We trained the classifier using TUD dataset and evaluated on PDC dataset, and vice versa.

TABLE VII
RECOGNITION ACCURACY COMPARISON ON PDC DATASET TRAINED BY TUD DATASET

	Classification criteria (%)	
	Strict	Soft
SVM (Normal)	46.34	72.70
SVM (Cost-relaxation)	48.06	74.57

TABLE VIII
RECOGNITION ACCURACY COMPARISON ON TUD DATASET TRAINED BY PDC DATASET

	Classification criteria (%)	
	Strict	Soft
SVM (Normal)	47.58	75.40
SVM (Cost-relaxation)	50.40	78.63

The classification results are shown in TABLES VII and VIII. We can see that the proposed method outperformed the standard SVM in both criteria.

V. CONCLUSION

In this paper, we proposed a classification training method which reduces "fatal" misclassifications by cost-relaxation of "tolerable" misclassifications for pedestrian orientation classification, named misclassification tolerable learning. We introduced a new class group *conceptually similar classes* to the one-against-all classification scheme. The conceptually similar classes are defined as classes whose class labels are similar to the positive class. In the case of pedestrian orientation classification, the conceptually similar classes are defined as classes whose class labels are neighboring orientation classes to the positive orientation class. A pedestrian orientation classifier was implemented by relaxing the misclassification cost for the conceptually similar classes and tuning the classifier for separating the positive class and the non-similar classes in one-against-all SVM training. We confirmed the classification performance of the proposed method by evaluating on TUD and PDC datasets.

Future work includes extension of the proposed concept to classifiers other than SVM, and application on other classification problems.

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