Classifier Ensembles with Trajectory Under-Sampling for Face Re-Identification

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Abstract: In person re-identification applications, an individual of interest may be covertly tracked and recognized based on trajectories of faces or other distinguishing information captured with video surveillance camera. However, a varying level of imbalance often exists between target and non-target facial captures, and this imbalance level may differ from what was considered during design. The performance of face classification systems typically declines in such cases because, to avoid bias towards the majority class (non-target), they tend to optimize the overall accuracy under a balance class assumption. Specialized classifier ensembles trained on balanced data, where non-target samples are selected through random under-sampling or cluster-based sampling, have been proposed in literature, but they suffer from loss of information and low diversity and accuracy. In this paper, a new ensemble method is proposed for generating a diverse pool of classifiers, each one trained on different levels of class imbalance and complexity for a greater diversity of opinion. Ensembles with Trajectory Under Sampling (EoC-TUS) allows to select subsets of non-target training data based on trajectories information. Variants of these ensembles can give more importance to the most efficient classifiers in identifying target samples, or define efficient and diverse decision boundaries by starting selection of trajectories from the farthest ones to the target class. For validation, experiments are conducted using videos captured in the Faces In Action dataset, and compared to several baseline techniques. The proposed EoC-TUS outperforms state-of-the-art techniques in terms of accuracy and diversity over a range of imbalance levels in the input video.

1 INTRODUCTION

Person re-identification is a video surveillance (VS) application where individuals are tracked and recognized at different time instants and/or locations over a network of cameras using information like faces, gaite and soft biometrics captured in video streams (Bedagkar-Gala and Shah, 2014). In face re-identification, faces from video streams are captured unobtrusively under uncontrolled conditions and recognized using a video-to-video face recognition (FR) system. Performance of these FR systems is severely affected by variations in pose and expression, as well as environmental conditions such as illumination, occlusion and blur. One important challenge in this application is that the number of reference face captures from target individuals is limited and greatly outnumbered by non-target ones. What's more, the level of imbalance observed during operations varies unpredictably over time. Therefore, the proportion of target to non-target captures is not balanced and differs from what is considered during enrolment.

Modular classification architectures are promising for FR in VS, where one or two-class classifiers are designed per target individual enrolled to the system (Pagano et al., 2014). In addition, ensembles of these binary classifiers per individual of interest have been successfully applied to face re-identification (Radtke et al., 2014; De-la Torre et al., 2015a; De-la Torre et al., 2015b). In order to define an accurate decision boundary, a one-class classifier requires a large number of representative target samples which is not often feasible in practice. In contrast, designing individual-specific ensembles with two-class classifiers require representative samples from both target and non-target classes. However, due to the high level of imbalance in data distribution, the performance of classifiers decline because they are often designed to

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optimize overall accuracy without taking into account the relative distribution of each class. Therefore, they become biased to correctly classifying the non-target class. In fact, designing with imbalanced data results in decision boundaries that move towards the minority class. To avoid this effect, most specialized approaches assume that the data is balanced for designing the classification system, and then prior knowledge of imbalance is used to bias decisions. However in practical VS applications, this imbalance is not usually known and varies over time.

It is well-known that classifier ensembles can increase accuracy and robustness over a single classifier by combining uncorrelated classifiers (Rokach, 2010). A diverse pool of classifiers can be generated to learn from subsets of imbalanced data (Galar et al., 2012) selected using random under-sampling in RUSBoost(Seiffert et al., 2010), synthetic minority oversampling in SMOTEBoost (Chawla et al., 2003), and cluster-based sampling (Yen and Lee, 2009; Li et al., 2013). These ensembles re-balance training data to avoid bias of performance towards the majority class. However, information loss is an issue in the case of under-sampling and high complexity is an issue for up-sampling approaches. What's more, the imbalance itself, as an inherent property of data distribution, is neglected, while using different skew levels is an additional source of diversity between classifiers in an ensemble.

Ensembles with random under-sampling (RUS) are designed by training several base classifiers with target samples and subsets of non-target samples selected randomly. These classifiers may be accurate because random subsets are representative of the whole data. However, accurate classifiers often fail to generate effective ensembles due to their lack of diversity. Ensembles with cluster under-sampling (CUS), in contrast, are designed using target samples and non-target samples assigned to clusters based on their proximity. These ensembles may be more effective than the RUS-based ensembles because they are combined from diverse classifiers designed on different parts of the feature space.

An application-based under-sampling method could be more effective than the general-purposed under-sampling methods described in literature in terms of diversity and accuracy of opinions.

In fact, grouping samples based on contextual information, rather than solely based on their proximity in the feature space, may have greater diversity. In addition, such non-target sampling technique may allow the majority samples to be ordered to produce efficient and diverse decision boundaries.

In many VS applications a tracker is used to follow and regroup objects in a camera's field of view according to trajectories for spatio-temporal recognition. For example, the tracker could follow the position of each person observed in the scene over consecutive frames, and the facial regions of interest (ROIs) of the same person are collected into a trajectory. Facial samples in a trajectory are captured under different operating conditions and consequently, they are dispersed in the feature space compared to the samples from a cluster of data. Therefore, a pool of classifiers trained on samples from trajectories may provide ensemble of classifiers with greater diversity and generalization.

In this paper, a new method is proposed to design individual-specific ensembles, where the pool of two-class classifiers is generated on data subsets that have different data imbalances and complexities. Training subsets contain a limited number of samples from target trajectory and a growing selection of samples from non-target trajectories to minimize the risk of information loss. Starting from one non-target trajectory for the first subset, the level of imbalance (and decision bound complexity) is increased for the next subsets by adding a number of non-target trajectories to the previous ones. Two variants are proposed to select among the non-target trajectories. In the first one, the trajectories are selected randomly and the contribution of each classifier is weighted based on its accuracy measured on a validation set. In the second variant, non-target trajectories are selected based on their proximity to the target trajectory. Since samples in a trajectory do not follow a mono-modal distribution, the Hausdorff distance (Edgar, 2007) is used to measure the distance between two trajectories. The accuracy and diversity of ensembles of classifiers designed with the proposed technique is compared to reference methods from literature using videos in the FIA dataset.

The rest of the paper is organized as follows. Section 2 presents a review of ensemble techniques for class imbalance in literature. Ensembles with trajectory under-sampling are described in Section 3. Experimental methodology is given in Section 4. This is followed by results and discussion in Section 5.

2 ENSEMBLES FOR CLASS IMBALANCE

Data class distributions are imbalanced in many real-world monitoring and surveillance applications such as face re-identification, watch-list screening, fraud detection and intrusion prevention. In these applications, the class with fewer samples is usually the tar-

get class and of more interest than the others.

Several approaches have been proposed in literature to handle imbalance as data-level, algorithm-level, and cost-sensitive methods. Data-level approaches use an additional process to re-balance the data distribution prior to or along with learning procedure. This group includes variations of up-sampling the minority class, under-sampling the majority class or the combination of both of them. Some of the baseline techniques in this category are SMOTE (synthetic minority over-sampling technique) (Chawla et al., 2002), cluster-based sampling (Yen and Lee, 2009), random under-sampling and One-sided Selection (OSS)(Kubat et al., 1997).

Algorithm-level methods are internal approaches that create or modify algorithms to bias the system accuracy towards the minority class (Wu and Chang, 2006). These methods require special knowledge of both the corresponding classifier and the application domain, comprehending why the classifier fails when the class distribution is uneven (Rokach, 2010).

Cost-sensitive approaches introduce uneven misclassification cost factors for the samples from different classes such that minimizing the total cost will provide a more robust algorithm for imbalance problem (Sun et al., 2007).

Ensembles of classifiers rely on the aforementioned methods to tune and combine several classifiers' performance under different conditions. The optimal accuracy-diversity trade-off is a key factor in the design of an accurate and effective ensemble of classifiers(Rokach, 2009). Even though there is no straightforward definition of diversity in literature, base classifiers are usually deemed diverse when their misclassification events are not correlated (Rokach, 2009). Therefore, neither of most accurate or least accurate classifiers create efficient ensembles. Diversity in generating ensembles to handle imbalance can be obtained by training base classifiers on target samples and different overlapping and balanced subsets of non-target data under-sampled randomly (Seiffert et al., 2010), or non-overlapping partitions created either randomly (Yan et al., 2003) or by clustering (Yen and Lee, 2009; Li et al., 2013). In sample-based approaches like random under-sampling (RUS) the samples are treated independently, while in cluster-based sampling techniques (Yen and Lee, 2009; Li et al., 2013) the samples are under-sampled based on their data distributions. For example, Li et al. (Li et al., 2013) propose an ensemble with cluster under-sampling (CUS), where each base classifier in the ensemble is trained on target samples and a cluster of the non-target class. The contribution of classifiers trained on the samples that are closer to the decision boundary is magnified by giving a higher weight to their vote in the final decision based on the distance between the mass centers of the non-target cluster used to train that classifier and target class.

In several VS applications like person re-identification, using contextual information to group samples could provide a better modelling of data from different people. For instance, the facial regions captured within trajectories are defined by different geometric and environmental conditions, so the facial region of interest (ROI) patterns in a trajectory may exhibit multi-modal distribution that are overlapping or dispersed in the feature space. Accordingly, a pool of 2-class classifiers that are trained on trajectories may provide more variability and diversity and provide better decision bounds.

In the case of cluster-based under-sampling, data samples are assumed to be defined by compact monomodal distributions. The classifiers trained on data clusters may be diverse but they are not necessarily accurate enough to create robust ensembles because data clusters may contain samples from different individuals and they are not representative of real data distribution. In RUS, the samples are selected from all over the space and even though the classifiers trained on them may be accurate, they are not necessarily diverse enough to create robust ensembles because these data subsets have similar distributions. Hence, an ensemble of classifiers designed with trajectories can generalize better than ensembles of classifiers trained on the clusters or randomly under-sampled data. In addition, using different data imbalances in designing classifiers increases the diversity and complexity of decision bounds among them. The diversity and accuracy of classifiers that are trained on growing skew levels and complexity of data is higher than the classifiers that are trained on the same skew level and complexity of samples at a time.

To validate these hypotheses, the ROI patterns of 6 facial trajectories belonging to 6 individuals (assume one target and 5 non-targets) from FIA [1] dataset (Goh et al., 2005) are mapped to 2D space using Sammon mapping (Sammon, 1969) (see Figure 1(a)).

Three ensembles of SVM classifiers with data subsets selected by random under-sampling (RUS), cluster-based under-sampling (CUS), and trajectory-based under-sampling (TUS) are created with growing skew [2] level between base classifiers (called EoC-GRUS, EoC-GCUS, EoC-GTUS). The first classifiers

[1] The experimental methodology and FIA data set used for validation is presented in Section 4.

[2] Skew $\lambda = \pi_p : \pi_n$ is defined as the proportion of positive (minority target) samples π_p to the negative (majority non-target) ones π_n .

in these ensembles are trained on balanced data and the imbalance levels of the subsets used to train the following classifiers are increased step by step. The clusters and trajectories are selected in random order. For CUS, the samples are regrouped into $k = 6$ (the same number of trajectories for fair comparison) clusters using k-means algorithm. In addition, the classifiers are combined with unweighted majority voting in all ensembles.

The decision boundary of three ensembles, EoC-GRUS, EoC-GCUS, EoC-GTUS, in Figure 1(b) show that EoC-GRUS has a decision boundary fitted to the target class and the decision boundary of EoC-GCUS invades the area of non-targets, while EoC-GTUS results in a decision boundary that covers target samples without invading the non-target class area.

The diversity and performance of all three ensembles are compared in Figure 2, where they are tested with several skew levels in test data. The results in Figure 2 support the hypotheses that EoC-GTUS maintains higher level of diversity, and provides higher accuracy over skew values. The classifiers in EoC-GRUS show the least diversity.

3 ENSEMBLES WITH TRAJECTORY UNDER-SAMPLING

The main objective of this paper is to design individual-specific ensemble of 2-class classifiers that allow to sustain a high level of accuracy and robustness over variations in levels of data imbalance. A novel ensemble generation technique is proposed in which base 2-class classifiers are trained on growing number of non-target trajectories. Varying this number maintains different levels of imbalance and complexity between data subsets.

This approach is specialized for VS applications like person re-identification, where faces or soft biometrics are captured and regrouped in terms of trajectories. A tracker assigns a track ID to each different person appearing in the scene. During consecutive frames, the tracker follows the positions of persons and regroups the face captures along each track into trajectories. Consider the faces captured in training video streams as $\mathbf{S}_{\text{tr}} = \{(\mathbf{x}_i, y_i, ID_i); i = 1, ..., M_{\text{tr}}\}$ where $y_i \in \{+1, -1\}$ indicates the class label, i.e. target (+1) or non-target (-1) classes, and ID_i is the track ID number assigned by the tracker to the face. Let ID^+ be the track ID number assigned by tracker to the target face. All target samples are grouped into a trajectory $\mathbf{t}^+ = \{(\mathbf{x}_p, y_p) \in \mathbf{S}_{\text{tr}} | ID_p = ID^+\}$. In the same way, the abundant non-target samples that are assigned the same track ID are grouped into a non-target trajectory as $\mathbf{t}_j^-$. By collecting all non-target trajectories into a set $\mathbf{T}^- = \{\mathbf{t}_j^-; j = 1, .., N^-\}$, the non-targets are under-sampled by eliminating a number of $\mathbf{t}_j^-$s from this set.

To generate design data with several skew levels, non-target samples in each subset are selected by accumulating trajectories incrementally without replacement. However, two important concerns arise with this ensemble generation technique. One is that the performance of base classifiers in the ensemble can be affected by the order of trajectories. Second is that, how the ensemble size and the number of trajectories for each classifier should be selected?

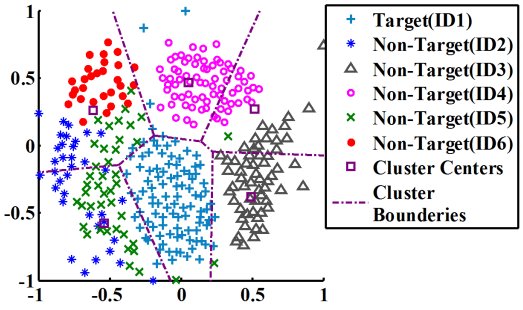
The order of trajectory selection can be random, or from the closest to the farthest or from the farthest to the closest. In random selection of trajectories, effectiveness of the classifiers in the ensemble cannot be guaranteed and very poor classifiers can exist in the final ensemble. This issue can be alleviated by reducing the impact of less accurate classifiers in the final decision of the ensemble.

Increasing the number of non-target samples and consequently imbalance level in data subsets that are used for training a classifier, moves its decision boundary towards target class (Liu et al., 2011). Therefore, starting from the closest non-target trajectory means starting from the fittest decision boundary to the target class. Therefore, adding trajectories to the existing ones aggravates the decision boundary of the following classifiers in the ensemble and reduces diversity among them. However, starting from the farthest decision boundary does not suffer from these problems.

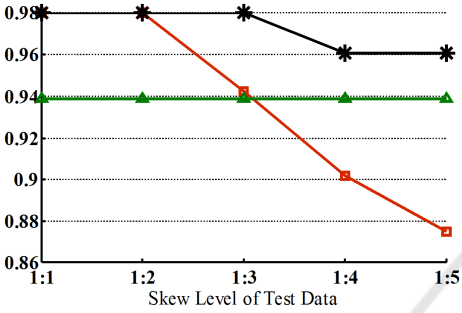
Two versions of ensembles with TUS are proposed in this paper that differ with respect to two factors: the way in which the non-target trajectories are selected, and the contribution of each classifier in the final prediction. These ensembles are described in Sub-sections 3.1 and 3.2.

TUS-ensemble can be designed by training a pool of classifiers equal to the number of non-target trajectories. In other words, the skew level of design data for each base classifier is approximately one level higher than the previous one. However, the ensemble size should be limited by using larger skew steps between base classifiers. In addition, bigger difference between skew levels of classifiers in the ensemble result in higher diversity among them.

To select the ensemble size, we determine the steps between skew levels based on the overall imbalance level of design data. The level of imbalance in a data distribution is typically calculated as the pro-



(a) Sammon mapping of a target trajectory and 5 non-target trajectories clustered using k-means with $k = 5$.



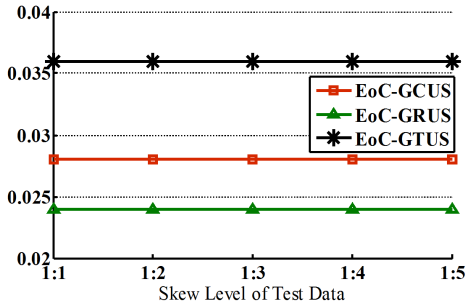
(b) Decision boundaries of 3 ensembles with GRUS, GCUS and GTUS.

Figure 1: Example of 2D data distribution and decision boundaries of an individual-specific ensembles on FIA data set.

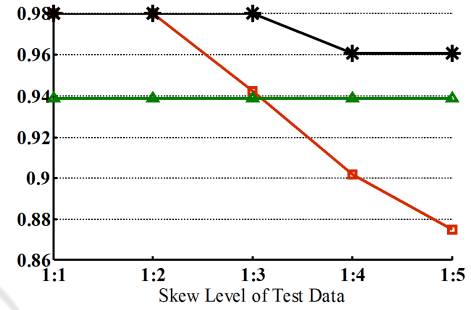
portion of overall number of non-target samples to the overall number of target ones (M^-/M^+). In this paper, the skew level is indicated in a different way based on the number of trajectories. Letting N^- be the number of non-target trajectories, N^+ be the number of target trajectories (typically $N^+ = 1$ in a single video sequence), and n_s as the desired skew level difference between two consecutive classifiers in the ensemble, the number of imbalanced sets to design classifiers in the ensemble n_e, is determined as:

$$n_e = \left\lfloor \frac{N^-}{n_s N^+} \right\rfloor \quad (1)$$

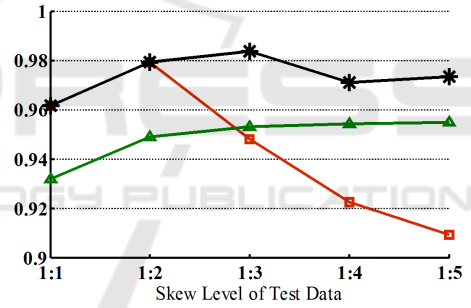
Considering the balanced case in addition to imbalanced ones, there are $n_e + 1$ classifiers in the ensemble. Defining the skew level of e^{th} classifier in the ensemble as λ_e, skew levels of data subsets in the ensemble are determined from the set: $\Lambda = \{\lambda_e | \lambda_0 = 1, \lambda_e = n_s \times e, e = 1,2,...,n_e\}$. As an example, if $n_s = 5$ and $N^-/5N^+ = 5.2$ for a dataset, the number of classifiers in the ensemble will be $n_e + 1 = 6$, with skew levels $\Lambda = \{1:1, 1:5, 1:10, 1:15, 1:20, 1:25\}$.



(a) Disagreement measure diversity level for growing skew levels.



(b) F_2 accuracy of GRUS, GCUS and GTUS.



(c) G-mean accuracy of GRUS, GCUS and GTUS.

Figure 2: Diversity and accuracy of ensembles produced with GRUS, GCUS and GTUS on FIA dataset mapped to the 2D space with Sammon mapping. The classifiers are tested by sets of data with varying skew levels from 1:1 to 1:5.

3.1 Random Trajectory Under-Sampling (RTUS)

In this version of EoC-TUS, in each design step, the non-target trajectories are selected randomly to train a new classifier for the ensemble. However, more importance is given to the component classifiers with better performance in classifying imbalanced data. In AdaBoost, RUSBoost and similar ensembles, a weight is assigned to each classifier based on its error rate e, as $\log((1-e)/e)$. In the case of classifying imbalanced data distributions, accuracy is not an appropriate measure to evaluate the performance

of a classifier. Therefore, in the proposed ensemble, the weight of each base classifier is set based on its performance measured using the F_2-measure, because this metric indicates classifier accuracy in correctly identifying the target samples.

The pseudo code of EoC-RTUS is presented in Algorithm 1. When a classifier is trained for the ensemble it is tested with a validation subset to determine its fusion weight. This validation subset should have the same level of imbalance (λ_e) as the training subset. Based on λ_e and the number of target samples in validation set (M^+_{val}), a number of non-target samples ($M^-_{\text{val}} = \lambda_e \times M^+_{\text{val}}$) is sampled randomly. The performance F_e of the $e-$th classifier in the ensemble is measured in terms of F_2-measure and its weight is assigned using:

$$w_e = \log\left(\frac{F_e}{1-F_e}\right) \tag{2}$$

This weight is then used to implement a for weighted combination of the ensemble and the fusion function could be decision-based or score-based.

3.2 Sorted Trajectory Under-Sampling (STUS)

Some non-target trajectories are more relevant than others, and can play a critical role in defining accurate class boundary. Samples of non-target trajectories that are closer to the target class are more relevant to define good classifier decision bounds (Stefanowski and Wilk, 2008). However, adding additional samples to them to design new classifiers does not maintain diversity and accuracy. Therefore, to generate EoC-STUS (Algorithm 2), first the non-target trajectories are sorted based on their proximity to the target class using Hausdorff distance (Edgar, 2007). It measures the distance between two sets of samples as the maximum of the minimum distances between pairs of elements from the two sets (Satta et al., 2011). The Hausdroff distance between all non-target trajectories and target trajectory is calculated as:

$$d_j = \max\{\min \parallel \mathbf{x}^+ - \mathbf{x}^- \parallel \mid \mathbf{x}^+ \in \mathbf{t}^+, \mathbf{x}^- \in \mathbf{t}^-_j\} \tag{3}$$

Given $D = \{d_j; j = 1,...,N^- | d_j \geq d_{j+1}\}$, the non-target trajectories are sorted into $\mathbf{T}^-_s = \{\mathbf{t}^-_j; j = 1,..,N^-\}$ in the same order as D. Then, for training the first classifier in the ensemble $\mathbf{t}^-_1$ is selected from $\mathbf{T}^-_s$ and for the next e-th classifiers ($e = 2,...,n_e$), $\{\mathbf{t}^-_k; k = 1,...,\lambda_e\}$) are used. Finally, the class of input data is voted among the predictions of component classifiers in the ensemble.

4 EXPERIMENTAL METHODOLOGY

The Face In Action (FIA) video database (Goh et al., 2005) has been used in our experiments to compare proposed EoC-RTUS and EoC-STUS for face re-identification with state of the art techniques, RUSBoost (Seiffert et al., 2010) and SeEn-SVM (Li et al., 2013) as well as two single SVM classifiers with RUS and without any preprocessing (SVM-RUS and SVM, respectively). The performance is also compared with EoC-RUS (ensemble of classifiers trained on balanced randomly selected subset of samples), EoC-CUS (ensemble of classifiers, each trained on one cluster), EoC-TUS (ensemble of classifiers, each trained on one trajectory), EoC-GRUS (ensemble of classifiers trained on growing number of random samples), and EoC-GCUS (ensemble of classifiers trained on growing number of clusters).

FIA dataset contains video sequences that emulate a passport checking scenario with 221 participants. The video streams are collected in different capture conditions such as pose, illumination and expression, in both indoor and outdoor environments in three sessions each of which three months later than the previous one. The participants are present before 3 cameras about 5 seconds, resulting in total of 18 video sequences. Only the video sequences captured with the frontal cameras in indoor environment have been used for experiments. We selected one video for design (training+validation), and two videos are merged for testing. Some individuals in the dataset appear in both design and test video streams (176 of them) and some (43) appear only in one of them. Target individuals for experiments are selected from those that appear in both videos and for each target individual, 100 non-target trajectories are selected from both groups.

Regions of interest (ROIs) have been extracted and rescaled using Viola Jones algorithm (Viola and Jones, 2001) from all selected video sequences in trajectories. Then, Multiresolution Gray-Scale and Rotation Invariant Local Binary Patterns (LBP) (Ojala et al., 2002) histograms have been extracted as features. The local image texture for LBP has been characterized with 8 neighbors on a 1 radius circle centred on each pixel. Finally, a feature vector with the length of 59 has been obtained for each ROI. Some examples of ROIs in a trajectory from this data set are presented in Figure 3.

A SVM with RBF kernel, $K(\mathbf{x}', \mathbf{x}'') = \exp(-\|\mathbf{x}' - \mathbf{x}''\|/2\sigma^2)$, is used as the base classifier in ensemble methods. The kernel parameter σ is set as the average of the mean minimum distance between any two training samples and the scatter

Algorithm 1: EoC-RTUS Algorithm.

Input:

- $\mathbf{S}_{\text{tr}} = \{(\mathbf{x}_i, y_i); i = 1, ..., M_{\text{tr}}\}$: Training set
- $\mathbf{S}_{\text{val}} = \{(\mathbf{x}_i, y_i); i = 1, ..., M_{\text{val}}\}$: Validation set
- $y_i \in \{+1, -1\}$: Class label of samples
- t^+: Target trajectory
- $\mathbf{T}^- = \{\mathbf{t}_j^-; j = 1, .., N^-\}$: Non-target trajectories
- $\mathbf{X}$: Input probe sample

Output: $Y \in \{+1, -1\}$: Predicted label of $\mathbf{X}$

// Design Phase //

1 Non-target trajectories are randomly shuffled into $\mathbf{T}_r^- = \{\mathbf{t}_j^-; j = 1, .., N^-\}$

2 The number of base classifiers N_e and their skew levels λ_e for $e = 1, 2, ..., n_e$: $n_e = \lfloor N^-/n_s N^+ \rfloor$, $N_e = n_e + 1$, $\Lambda = \{\lambda_e | \lambda_0 = 1, \lambda_e = n_s e\}$

3 **for** $e = 0, .., n_e$ **do**

- i Collect a subset of $\mathbf{T}_r^-$ into $\mathbf{T}_{r,e}^- = \{\mathbf{t}_k^-; k = 1, ..., \lambda_e\}$
- ii Train a classifier C_e on $\mathbf{T}_{r,e}^-$ and $\mathbf{t}^+$
- iii under-sample the validation set $\mathbf{S}_{\text{val}}$ randomly to λ_e level
- iv $F_e \leftarrow F_2$-measure attained by C_e on the validation subset
- v Set the weight of C_e as: $w_e = \log(\frac{F_e}{1-F_e})$

// Test Phase //

4 **for** $e = 0, .., n_e$ **do**

- $h_e(\mathbf{X}) \leftarrow$ Output of C_e (classification score or decision) on $\mathbf{X}$.

5 Combine the predictions of classifiers: $Y = \text{sign}\left(\sum_{e=0}^{n_e}(w_e h_e(\mathbf{X}))\right)$

radius of the training samples in the input space (Li et al., 2008). The scatter radius is calculated by selecting the maximum distance between the training samples and a point corresponding to the mean of training samples. We used the LibSVM implementation of (Chang and Lin, 2011).

Six versions of EoC-STUS and EoC-RTUS have been implemented. In three versions (EoC-RTUS-1, EoC-STUS-1A and EoC-STUS-1D) n_s is selected as 1 so that the number of SVMs will be the same as the maximum number of non-target trajectories (100) and the skew levels of data subsets used to train classifiers are determined from $\Lambda_{\text{tr}} = \{1:1, 1:2, 1:3, ..., 1:100\}$. In EoC-STUS-1A and EoC-STUS-1D, non-target trajectories are sorted based on their distance form target trajectory from the closest to the farthest and from the farthest to the closest ones, respectively. In the other three versions (EoC-RTUS-5, EoC-STUS-5A and EoC-STUS-5D) n_s is selected as

Algorithm 2: EoC-STUS Algorithm.

Input:

- $\mathbf{S}_{\text{tr}} = \{(\mathbf{x}_i, y_i; i = 1, ..., M_{\text{tr}}\}$: Training set
- $y_i \in \{+1, -1\}$: Class label of samples
- t^+: Target trajectory
- $\mathbf{T}^- = \{\mathbf{t}_j^-; j = 1, .., N^-\}$: Non-target trajectories
- $\mathbf{X}$: Input probe sample

Output: $Y \in \{+1, -1\}$: Predicted label of $\mathbf{X}$

// Design Phase //

1 The Hausdorff distance (Eq. 3) between all $\mathbf{t}_j^-$s and $\mathbf{t}^+$ are sorted into $D = \{d_j; j = 1, ..., N^- | d_j \geq d_{j+1}\}$

2 Non-target trajectories are sorted based on D into $\mathbf{T}_s^- = \{\mathbf{t}_j^-; j = 1, .., N^-\}$

3 The number of base classifiers N_e and their skew levels λ_e for $e = 1, 2, ..., n_e$: $n_e = \lfloor N^-/n_s N^+ \rfloor$, $N_e = n_e + 1$, $\Lambda = \{\lambda_e | \lambda_0 = 1, \lambda_e = n_s e\}$

4 **for** $e = 0, .., n_e$ **do**

- i Collect a subset of $\mathbf{T}_s^-$ into $\mathbf{T}_{s,e}^- = \{\mathbf{t}_k^-,\ k = 1, ..., \lambda_e\}$
- ii Train a classifier C_e on $\mathbf{T}_{s,e}^-$ and $\mathbf{t}^+$

// Test Phase //

5 **for** $e = 0, .., n_e$ **do**

- $h_e(\mathbf{X}) \leftarrow$ Output of C_e (classification score or decision) on $\mathbf{X}$.

6 Combine the predictions of classifiers: $Y = \text{sign}\left(\sum_{e=0}^{n_e}(h_e(\mathbf{X}))\right)$

5 and the number of SVMs is selected as 21 obtained based on Eq. 1. The skew levels of data subsets used to train classifiers in these three versions are determined from $\Lambda_{\text{tr}} = \{1:1, 1:5, 1:10, 1:15, 1:20, ..., 1:100\}$. The number of SVMs in the RUSBoost has been also set to 21 for the sake of fair comparison.

The number of classifiers in the SeEn-SVM is given by 2^{n_0}, where $n_0 = \min_n\{|q - 2^n|, n = 1, 2, ...\}$, $q = {}^{M^-}/_{5M^+}$. The number of classifiers in EoC-RUS, EoC-GRUS, EoC-CUS, EoC-GCUS and EoC-TUS are set to 100 to be comparable to EoC-RTUS-1, EoC-STUS-1A and EoC-RTUS-1D. In our experimental protocol, the results have been averaged by alternating the target individual among overall 10 target individuals in each round of the evaluation process, and for each target individual, the algorithms have been replicated 10 times using 5-fold cross-validation to generate design data; 2-folds for training and 3 folds for validation. In addition, in each replication, the test data has been under-sampled randomly to create subsets with different skew levels $\Lambda_{\text{test}} = \{1:1, 1:20, 1:50, 1:100\}$ to evaluate the robustness of each approach over varying skew levels during operation.

Figure 3: Examples of 70× 70 pixels ROIs in a trajectory captures with camera 3, during section one for ID004.

The performance of the new and reference systems is assessed in the Receiver Operating Curve (ROC) and Precision-Recall spaces. Performance metrics that rely on the simple accuracy are ill-suited for evaluating 2-class classification problems with imbalanced distributions. In fact, ROC space does not reflect the impact of imbalance (Fawcett, 2006). False positive rate (FPR) is defined as the proportion of misclassified non-targets to the number of non-targets. With highly imbalanced data, FPR stays small and therefore ROC curve tends to locate at the left part of ROC space. In contrast, precision measures the proportion of correctly classified target class samples to the number of samples that are predicted as target class. Recall or true positive rate (TPR) measures the proportion of target samples that are predicted correctly to overall number of target samples. To avoid calibration of decision threshold systems are compared using two global scalar metrics: area under receiver operating (AUC) and area under the precision-recall curve (AUPR).

Several measures of ensemble diversity have been introduced in literature (Kuncheva and Whitaker, 2003) that are mostly calculated based on the relation between the predictions of pairs of classifiers on a given validation set of data. Disagreement measure indicates the ratio of correct predictions of classifiers by taking into account only those correct predictions that are not from the same classifiers. However, due to abundance of samples in one class in imbalanced distribution of classes, the diversity measures mostly present the level of disagreement between classifiers on identifying majority class (or non-targets). This problem can be alleviated by measuring the diversity level on balanced distribution of classes or by giving higher significance to the minority (target) samples. In order to reduce significance of non-target samples in measuring diversity, the disagreement metric is measured here only on target samples to indicate the level of disagreement between classifiers on correctly classifying the target samples. Therefore, the value of this metric contains information on both accuracy and diversity of base classifiers in the ensemble on target samples. Considering D_m and D_n as decisions of a pair of classifiers on a validation data, the pairwise disagreement measure $Dis_{m,n}$ between them is calculated based on diversity matrix in Table 1 as:

$$Dis_{m,n} = \frac{D^{cw} + D^{wc}}{D^{cw} + D^{wc} + D^{cc} + D^{ww}} \quad (4)$$

Disagreement measure varies between 0 and 1, value of 1 representing the most desirable diversity level. For N_e classifiers in the ensemble, Dis_{av} is obtained from:

$$Dis_{av} = \frac{2}{N_e(N_e-1)} \sum_{m=1}^{N_e-1} \sum_{n=m+1}^{N_e} Dis_{m,n} \quad (5)$$

Table 1: Diversity measure matrix.

	D_n correct	D_n wrong
D_m correct	D^{cc}	D^{cw}
D_m wrong	D^{wc}	D^{ww}

5 RESULTS AND DISCUSSION

Tables 2 and 3 present the average AUPR and AUC performance of the proposed EoC-RTUS and EoC-STUS techniques compared to several baseline techniques. The average AUPR values are significantly higher for EoC-TUS and EoC-CUS than other systems over all test-set skew levels. However, their AUC value is low because they are successful in correctly classifying target class in expense of misclassifying higher number of non-target samples. EoC-RTUS-1, EoC-STUS-1D, EoC-STUS-5 and RUSBoost result in a comparable AUC, while EoC-STUS-5D is more efficient in recognizing target samples in terms of AUPR. EoC-TUS outperforms EoC-CUS and EoC-RUS in terms of both AURP and AUC. These results support the hypothesis given in Section 3 that using an application-based contextual information like tracking information to under-sample data

result in a more efficient ensemble of classifiers compared to CUS and RUS.

Most of the ensembles in this experiment are robust to different skew levels in test data in terms of AUC and AUPR. This suggest that these ensembles can be optimized by proper selection of their decision threshold in different skew levels of test data. In contrast, the performance of SVM, SVM-RUS and RUSBoost in terms of AUPR declines considerably as the imbalance level of test data increases.

For all three under-sampling methods (RUS, CUS and TUS), growing imbalance levels between classifiers in GRUS, GCUS and GTUS result in a more desirable AUC and AUPR performance. Among different versions of EoC-GTUS, it is observed that ensembles that are designed with non-target trajectories gradually learned in a descending order w.r.t. their distance from target trajectory outperform ensembles designed with non-target trajectories learned in an ascending order.

In Figure 4, RUSBoost and EoC-STUS-5D maintain the highest level of diversity. Classifiers in EoC-STUS-5D and EoC-RTUS-5 are more diverse than other ensembles including SeEn-SVM and EoC-GRUS, proving that training classifiers on growing imbalance levels of trajectories starting from the farthest ones is more effective than RUS, GRUS, CUS and GCUS.

It is worth mentioning that, eventhough EoC-RTUS-1 and EoC-STUS-1 are implemented with larger ensemble sizes, they are not as effective as EoC-RTUS-5 and EoC-STUS-5 from both accuracy and diversity view points because bigger steps in skew level and complexity of decision boundaries generate more pair-wise diversity among classifiers and consequently more effective ensembles.

In terms of computation complexity, training runtime of ensembles in this experiment is shown in Figure 5. Figure 5(a) compares the runtime of ensembles with the same size as $N^- = 100$ and Figure 5(b) compares the runtime of ensembles with the same size as $N_e = 21$. In Figure 5(a), GRUS, GCUS and GTUS take more time for training compared to RUS, CUS and TUS. This was expected because all classifiers in RUS, CUS and TUS are trained on a balanced set of samples, while the size of training subsets in GRUS, GCUS and GTUS is growing from the first classifier to the last one.

For both ensemble sizes, since EoC-RTUS requires a validation step for each classifier in the ensemble, the runtime of EoC-RTUS is longer than EoC-STUS. EoC-STUS with sorting trajectories in ascending order of their distances to the target trajectory take more training time compared to EoC-STUS with sorting trajectories in descending order. RUSBoost and SeEn-SVM train the classifiers on a balanced number of samples. However, in each iteration of RUSBoost, a validation process is carried out that tests the classifier on all samples and this makes RUSBoost time consuming.

6 CONCLUSION

In this paper, a novel technique is proposed for the design of individual-specific ensembles to address the class imbalance problem in person re-identification applications. In ensembles with trajectory under-sampling (EoC-TUS), training subsets contain samples from target trajectory and a growing selection of samples from non-target trajectories to minimize the risk of information loss. Instead of using general-purpose under-sampling techniques such as random or cluster-based under-sampling, contextual information (i.e., trajectory structure) is exploited to under-sample from an abundance of non-target data to design diverse ensembles of 2-class classifiers. Starting from one target and non-target trajectory for the first subset, the level of imbalance and decision bound complexity is increased for the next subsets by adding non-target trajectories to the previous ones. Variants of these ensembles can give more importance to the most efficient classifiers in recognizing target samples, or define efficient and diverse decision boundaries by starting selection of trajectories from the farthest ones to the target class. Experimental results obtained using videos of the FIA data set indicate that the proposed EoC-TUS outperforms several baseline techniques over a range of test-set imbalance levels. Although using all non-target trajectories eliminate the risk of information loss, not all samples are informative and yield better generalization generalization. In future work, a more sophisticated selection scheme that account for the multi-modal distribution of trajectories will be investigated to select trajectories such that ensembles maintain higher diversity while reducing amount of redundant data and training time.

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Table 2: Average of AUPR performance of proposed and baseline techniques over 10 target individuals, each with 10 replications, over class imbalance values in the test-set.

Classification System	λ_{test}	**1:1**	**1:20**	**1:50**	**1:100**
SVM		0.61 ± 0.010	0.28 ± 0.014	0.22 ± 0.013	0.19 ± 0.013
SVM-RUS		0.75 ± 0.018	0.46 ± 0.027	0.37 ± 0.028	0.31 ± 0.027
EoC-RUS		0.48 ± 0.019	0.45 ± 0.019	0.44 ± 0.019	0.43 ± 0.019
EoC-CUS		$\mathbf{0.87 \pm 0.012}$	$\mathbf{0.87 \pm 0.011}$	$\mathbf{0.87 \pm 0.011}$	$\mathbf{0.87 \pm 0.011}$
EoC-TUS		$\mathbf{0.87 \pm 0.012}$	$\mathbf{0.87 \pm 0.011}$	$\mathbf{0.88 \pm 0.011}$	$\mathbf{0.88 \pm 0.011}$
EoC-GRUS		0.47 ± 0.019	0.47 ± 0.019	0.47 ± 0.019	0.47 ± 0.019
EoC-GCUS		0.58 ± 0.023	0.58 ± 0.023	0.58 ± 0.023	0.58 ± 0.023
RUSBoost (Seiffert et al., 2010)		0.79 ± 0.020	0.47 ± 0.020	0.37 ± 0.020	0.30 ± 0.020
SeEn-SVM (Li et al., 2013)		0.70 ± 0.022	0.46 ± 0.022	0.46 ± 0.022	0.46 ± 0.022
EoC-RTUS-1		0.64 ± 0.022	0.64 ± 0.022	0.64 ± 0.022	0.64 ± 0.022
EoC-STUS-1A		0.45 ± 0.019	0.45 ± 0.019	0.45 ± 0.019	0.45 ± 0.019
EoC-STUS-1D		0.65 ± 0.015	0.65 ± 0.015	0.65 ± 0.015	0.65 ± 0.015
EoC-RTUS-5		0.65 ± 0.029	0.65 ± 0.029	0.65 ± 0.029	0.65 ± 0.029
EoC-STUS-5A		0.56 ± 0.020	0.56 ± 0.020	0.56 ± 0.020	0.56 ± 0.020
EoC-STUS-5D		$\mathbf{0.75 \pm 0.017}$	$\mathbf{0.75 \pm 0.017}$	$\mathbf{0.75 \pm 0.017}$	$\mathbf{0.75 \pm 0.017}$

Table 3: Average of AUC performance of proposed and baseline techniques over 10 target individuals, each with 10 replications, over class imbalance values in the test-set.

Classification System	λ_{test}	**1:1**	**1:20**	**1:50**	**1:100**
SVM		0.37 ± 0.014	0.37 ± 0.014	0.37 ± 0.014	0.37 ± 0.014
SVM-RUS		0.44 ± 0.023	0.44 ± 0.023	0.44 ± 0.023	0.44 ± 0.023
EoC-RUS		0.52 ± 0.021	0.52 ± 0.021	0.52 ± 0.021	0.52 ± 0.021
EoC-CUS		0.50 ± 0.030	0.51 ± 0.029	0.51 ± 0.029	0.51 ± 0.029
EoC-TUS		0.60 ± 0.027	0.61 ± 0.026	0.61 ± 0.026	0.61 ± 0.026
EoC-GRUS		0.54 ± 0.022	0.54 ± 0.022	0.54 ± 0.022	0.54 ± 0.022
EoC-GCUS		0.60 ± 0.020	0.59 ± 0.019	0.60 ± 0.019	0.60 ± 0.019
RUSBoost (Seiffert et al., 2010)		$\mathbf{0.70 \pm 0.021}$	$\mathbf{0.69 \pm 0.021}$	$\mathbf{0.69 \pm 0.021}$	$\mathbf{0.69 \pm 0.021}$
SeEn-SVM (Li et al., 2013)		0.65 ± 0.021	0.66 ± 0.020	0.66 ± 0.020	0.66 ± 0.020
EoC-RTUS-1		0.68 ± 0.023	0.68 ± 0.023	0.68 ± 0.023	0.68 ± 0.023
EoC-STUS-1A		0.52 ± 0.018	0.52 ± 0.017	0.52 ± 0.017	0.52 ± 0.017
EoC-STUS-1D		$\mathbf{0.69 \pm 0.020}$	$\mathbf{0.69 \pm 0.020}$	$\mathbf{0.69 \pm 0.020}$	$\mathbf{0.69 \pm 0.020}$
EoC-RTUS-5		0.63 ± 0.027	0.63 ± 0.027	0.63 ± 0.027	0.63 ± 0.027
EoC-STUS-5A		0.57 ± 0.019	0.58 ± 0.017	0.58 ± 0.018	0.58 ± 0.018
EoC-STUS-5D		$\mathbf{0.69 \pm 0.015}$	$\mathbf{0.70 \pm 0.014}$	$\mathbf{0.69 \pm 0.014}$	$\mathbf{0.69 \pm 0.014}$

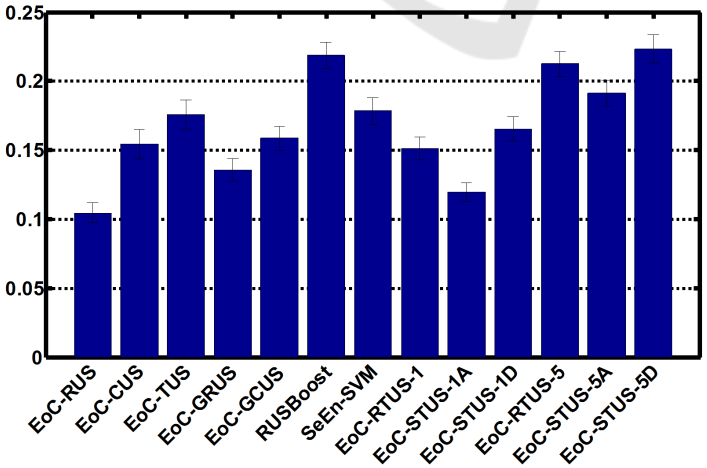
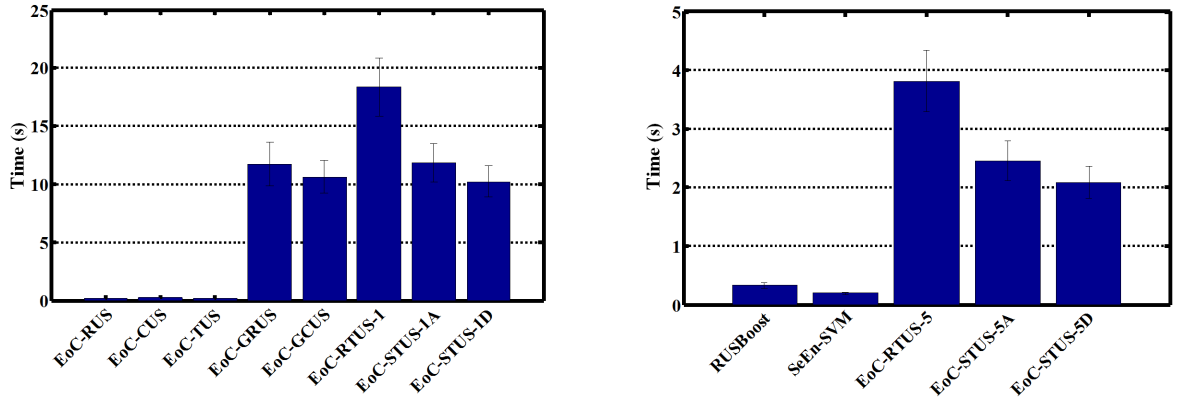


Figure 4: Average of diversity (disagreement measure) of proposed and baseline techniques over 10 target individuals and 10 replications. Dispersion measures are standard errors of the sample mean.



(a) Average training time of ensembles of size $N^- = 100$.

(b) Average training time of ensembles of size $N_e = 21$.

Figure 5: Average of training runtime of proposed and baseline techniques over 10 target individuals and 10 replications. Dispersion measures are standard errors of the sample mean.

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