Cross-context analysis for long-term view-point invariant Person Re-identification via soft-biometrics using Depth sensor

Athira Nambiar[1], Alexandre Bernardino[1] and Jacinto C. Nascimento[1]
[1]*Institute for Systems and Robotics, Instituto Superior Técnico, Av. Rovisco Pais, 1, 1049-001, Lisbon, Portugal*
{*anambiar, alex, jan*}*@isr.ist.utl.pt*

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Abstract: We propose a novel methodology for cross-context analysis in person re-identification using 3D features acquired from consumer grade depth sensors. Such features, although theoretically invariant to perspective changes, are nevertheless immersed in noise that depends on the view point, mainly due to the low depth resolution of these sensors and imperfections in skeleton reconstruction algorithms. Thus, the re-identification of persons observed on different poses requires the analysis of the features that transfer well its characteristics between view-points. Taking view-point as context, we propose a cross-context methodology to improve the re-identification of persons on different view-points. On the contrary to 2D cross-view re-identification methods, our approach is based on 3D features that do not require an explicit mapping between view-points, but nevertheless take advantage of feature selection methods that improve the re-identification accuracy.

1 INTRODUCTION

Long-term person re-identification (Re-ID) is one of the most interesting tools in the realm of intelligent video-surveillance. It consists of identifying an individual in different locations at significantly different time instants, and assigning her/him the same identifier (Gong et al., 2014; Bedagkar-Gala and Shah, 2014). There are many fundamental challenges associated with the task of long-term re-identification, wherein the surveillance period extends for many days, weeks or more. Among the biggest challenges are the change in appearance and view-points.

In this paper, we address the first challenge of appearance variation via leveraging soft biometric features (like human gait and anthropometrics), which are more stable over long periods than the appearance cues. The recent availability of low-cost depth sensors opens the possibility for improved surveillance systems on indoor spaces. Exploiting the 3D skeleton tracking functions of these sensors, we extract anthropometric and gait-based features from the target persons. The second challenge i.e., variation in viewpoint, causes the features to vary among different poses. Albeit the skeleton coordinates provided by kinect data are, in principle, view-point invariant (can be normalized to a canonical view-point by a roto-translation transformation), their computation (skeleton reconstruction) highly depends on the view points and self-occlusions. In other words, even though signal is the same, the noise level varies depending on the view-points and self occlusions i.e., data quality highly depends on the view-point (Nambiar et al., 2017b). For instance lateral views of a person are more subject to self-occlusion thus imposing larger amounts of noise in the occluded parts of the persons body. Frontal views, on the contrary, have more noise in the arms and legs distances of walking people. In order to tackle this view-point issue whilst maintaining the quality of the feature data, the concept of ‘Context’ was proposed in the work of (Nambiar et al., 2017a). Based on the concept that “the characteristics of a person that best correlate to its identity depend strongly on the view point ”, in that work they associated context to the viewing direction of walking people, and then selected the best features for each case. A method named *Context-aware ensemble fusion* has been proposed in that work, by choosing the relevant potential features in each view-point and thus training individual classifiers for each context. However, that method relies on the assumption of the existence of samples of all subjects in all view-points. This may not be possible to implement in less controlled (on-the-wild) surveillance scenarios where person samples are scarce and may not be possible to acquire in some view points. Thus, we extend that work for the data-insufficient case, i.e. when it can not be assured that all view points in the gallery have samples of all pedestrians, and denote it Cross-context ensemble fusion. For instance, it is frequent that some camera acquires a large sample set (e.g: camera facing to long corridor acquires long sequence) whereas some other camera collects only a small sample set (e.g: Camera facing to a lift/ door may get only short footage). This will be greatly reflected in the number of training samples available in the gallery for the Re-ID matching process. In order to tackle such situations, we propose a novel idea called *'cross-context'* analysis. Since the best discriminating features will be different in different contexts, we propose to employ a feature selection strategy a priori in order to identify the features that represent well the identity of the person in pairs of contexts. This data transfer among contexts via feature selection is the crux of our cross-context proposal.

Various experimental case studies on cross-context analysis (viz., full cover, sparse cover and single-cover) are carried out in order to verify the clear impact of the amount of gallery samples in the cross-context approach. In addition to that, we conducted yet another improvement of the study in comparison with the work of (Nambiar et al., 2017a), named as 'switching of contexts'. Since they always used straight line walkings for both testing and training, it was not clear how well the system can re-identify people while changing the walking direction within a gait cycle. In order to analyze this criteria, we analyze circular path movement as an instance of such a context-switching scenario.

The rest of the paper is organized as follows. Section 2 presents the state-of-the-art research in the field. Section 3 details our proposed approach followed by Section 4 that describes experimental results. Finally, Section 5 concludes the paper, also by enumerating some future perspectives.

2 RELATED WORK

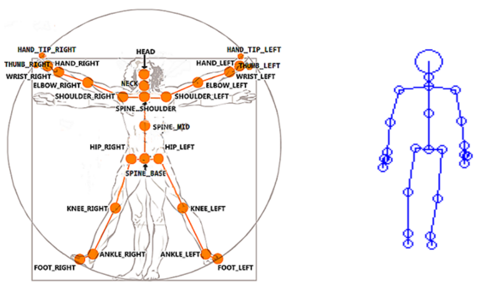
The concept of context has been incorporated in many diverse fields including re-identification. Heterogeneous contextual information (e.g. activity, attributes, clothing) have been used in (Zhang et al., 2014) to fuse the notion of contexts by means of a a generic entity resolution framework called RelDC. Also, some other works viz., (Leng et al., 2015; Garcia et al., 2015) have used 'context' (information of k-common nearest neighbors) wherein they used it in addition to the content information. The use of viewpoint as a context, has been reported in (Geng et al., 2010; Nambiar et al., 2017a). In (Geng et al., 2010), it is used a context-aware multi-biometric fusion, leveraging gait and face for human identification and by considering two important context factors i.e., view angle and subject-to-camera distance. However, in (Nambiar et al., 2017a), the contexts were considered as the view-points defined in the angular space. The novelty of that work was the feature selection and the individual classifier learning for different viewpoints. However, the proposal was inadequate to deal with the practical data deficient scenarios. In this work, we build upon the proposal of (Nambiar et al., 2017a) towards cross-context or cross-view analysis.

Only limited works have been reported on cross-view analysis in the literature, and only in 2D. For instance, in (Lisanti et al., 2017), they proposed a method to overcome the drastic variability of appearance in different camera views via Multi channel-Kernel canonical correlation analysis (KCCA), where a set of projection spaces are learned. In (Chen et al., 2016) Cross-View Discriminant Component Analysis (CVDCA) was proposed with the purpose to transform the features of the different views points to a common space where discriminative features are extracted for the Re-ID. In (Dai et al., 2017) a cross-view semantic projection learning (CSPL) approach was reported. Here the proposed methodology was able to jointly learn both the semantic projection and association functions that capture the relationship between the semantic representations of the same pedestrian from cross-views. Nevertheless, all of them were addressing the short-term person Re-ID problem in 2D. Also, the above methods require some sort of projection mechanism for the feature transformation from different views to a common space, thus requiring a mapping to model correlations in different views. However in our proposal, no feature projection is needed, and thus no feature mapping for correlation is required. Instead, features have to be select, to obtain the most relevant/discriminative features for each context (i.e., view point). Also, in our work, we envisage cross-view analysis towards long-term person Re-ID task by exploiting more stable 3D biometric features.

There have been some works proposed in the re-identification paradigm, utilizing 3D data, mainly leveraging Kinect sensor. The main attempt of extracting Kinect-based soft biometric features, was presented in (Barbosa et al., 2012). In that work, they utilized static body information i.e., skeleton and surface based features, in the frontal view. Based on that work, many other works reported later other features as well i.e., stride and arm kinematics (Gabel et al., 2012), anthropometric and angles of lower joints (Andersson and de Araújo, 2015) and static and dynamic statistics (Gianaria et al., 2014; Nambiar et al., 2017b). All of these works collected data in a controlled predefined single direction say, either frontal or lateral. The works of (Nambiar et al., 2017b; Nambiar et al., 2017a) were the first works explicitly addressing view-point invariant Re-ID scenario with 3D data by collecting depth camera sequences of people walking in different directions (each view-point named as a 'context'). Now, building upon these works we extend them by proposing cross-view in 3D, towards a realistic scenario of of sparse galleries, i.e. where not all contexts contain samples from all persons. Thus we try to answer the question of *'how to tackle the insufficiency of data samples?'*. As we mention in the forthcoming section, we propose the concept of cross-context via feature selection in order to transfer the information across different contexts. To the best of our knowledge, this paper makes the first work in cross-view analysis towards long term Re-ID leveraging 3D data.

3 PROPOSED METHOD

In this section, we explain our proposed methodology of cross-context analysis, as the special case of context-aware Re-ID scenario. In particular, in Section 3.1, we first explain the basic methodology associated with the baseline Context-aware ensemble fusion technique as described in (Nambiar et al., 2017a). Then, we particularize on our novel proposal of Cross-context ensemble framework in Section 3.2.



(a) (b)

Figure 1: (a) Skeleton positions relative to the human body[1] (b) A sample skeleton body visualization from our collection.

[1]For body joint types and enumeration, refer to the link: `https://msdn.microsoft.com/en-us/library/microsoft.kinect.jointtype.aspx`

3.1 Context-aware ensemble fusion framework

As we already mentioned in the Section 2, we built upon the work of (Nambiar et al., 2017a) i.e., *context-aware ensemble fusion framework*, to extend it towards cross-context analysis. The essence of context-aware fusion proposal was the arrangement of gallery samples according to the context, and adaptive selection of the potentially relevant features in order to train context-specific individual classifiers.

Let the sample data be represented as X, which is basically the raw data i.e., joint positions acquired via Kinect depth sensor (see Fig.1), and the extracted features be denoted by F. Based on the dataset characteristics of viewpoint l ($l = 1,..,L$), gait cycle m ($m = 1,..,M$) and the person ID n ($n = 1,..,N$) each individual sample data and the corresponding extracted feature can be denoted as $x_{lmn} \in \mathbb{R}^{j \times z}$ and $f_{lmn} \in \mathbb{R}^{D}$ respectively [2]. In particular, we reimplemented 74 features similar to the (Nambiar et al., 2017a), both anthropometric and gait features. Basically, two kinds of features were extracted: *(i)* Anthropometric features are associated to the static physical features defining the body measurements (e.g., height, arm length, upper torso length, chest size etc.) whereas Gait features are associated to the dynamic features defining the kinematics in walking (e.g., angles at various body joints,the distance between various right-left limbs, the relative position of body joints, stride length etc.). Totally, the feature set consists of 7 anthropometric features and 67 gait features (See (Nambiar et al., 2017a) for the list of features extracted).

One interesting characteristic of this proposal is the partition of the data in different galleries, one for each context ($F_l = \{f_{lmn}\}$ where l = *1,... L*, m = *1, ... M*, n = *1, ..., N*). Thus for each person n, there will be $M \times L$ examples in the gallery. Then, according to context, the samples are grouped and feature selection will be carried out to select the respective features. Assume $S_l \in \{0,1\}^D$ represents the binary vector enumerating the selected set of features for a particular context l, with a 1 in the position of the selected features and zeros otherwise. Similarly to (Nambiar et al., 2017a), we have used one of the most popular Feature Selection (FS) techniques, the Sequential Forward Selection (SFS) as an instance (Whitney, 1971). It works iteratively by adding features to an initial subset, seeking to improve the Re-ID measurement.

A context detector module analyses the walking

[2]Note that j refers to the number of joints in a skeleton model where j=25; z represents the dimension of each joint co-ordinate i.e., z=3 ; D if the total number of features in a feature vector i.e., D=74.

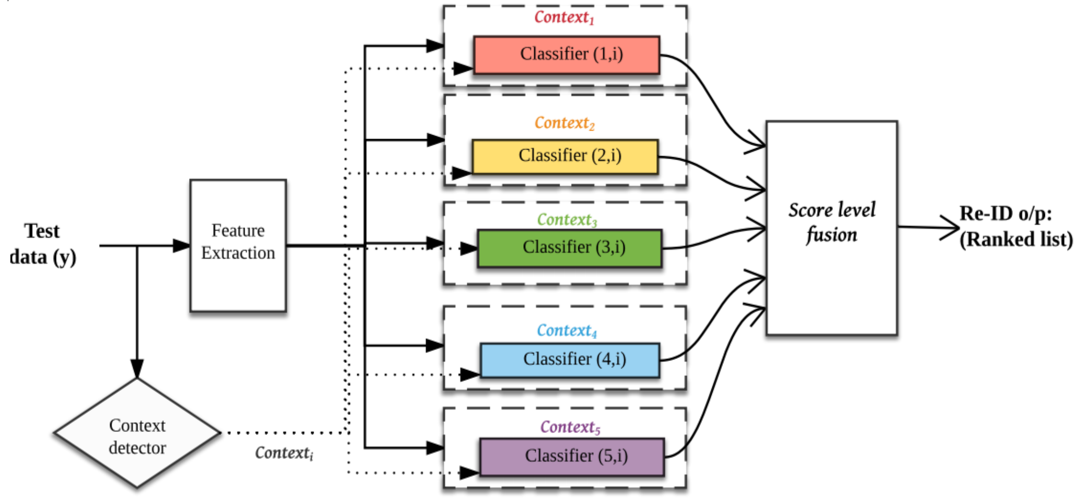


Figure 2: Cross-context ensemble fusion framework: A diagrammatic overview of cross-context analysis is given above. Individual cross-context classifiers are trained based on the learned feature selection carried out between the probe context i, and the gallery context of interest. Then, based on score level fusion overall Re-ID result is given as output.

direction of the person and uses the Gallery with the closest viewpoint or the two neighboring Galleries. Hence, whenever the test context is known to the system, it will direct the Re-ID process towards the corresponding gallery context in order to facilitate a fast and accurate person matching. Based on these individual context feature selection, Nearest Neighbor (NN) classifiers are designed according to the following. Given a new test sample described by features f with d being the index of the feature, the match score $\mathrm{C_{lmn}}^{(\mathrm{d})}(\mathrm{f})$ with the Gallery sample is computed as:

$$C_{\mathrm{lmn}}{}^{(\mathrm{d})}(f) = |f^{(\mathrm{d})} - f_{\mathrm{lmn}}{}^{(\mathrm{d})}|.S_{\mathrm{l}}{}^{(\mathrm{d})} \tag{1}$$

Then, score-level fusion brings the overall score of all the selected features:

$$C_{\mathrm{lmn}}(f) = \sum_{d} C_{\mathrm{lmn}}{}^{(\mathrm{d})}(f) \tag{2}$$

Then, the best matching score is computed by calculating the minimum matching score (smaller the similarity score, higher the matching).

$$C_{\mathrm{ln}}(f) = \min_{m} C_{\mathrm{lmn}}(f) \tag{3}$$

If more than one context is selected (two neighboring contexts), then linear interpolation technique will be carried out in order to give adaptive weights to each context Re-ID score which is described in (Nambiar et al., 2017a) as 'Context-aware score level fusion'.

3.2 Cross-context ensemble fusion framework

The very basic concept behind our idea for cross-context analysis is to solve the issue of data deficiency in the gallery context corresponding to the current context. Whereas in (Nambiar et al., 2017a), the number of samples per person in each context l i.e., M was considered constant, in our case we consider that the number can vary and can actually be zero in some contexts. So, the number of samples per per person in a certain context is denoted by M_{ln}. This is a much more realistic case in practical situations in-the-wild where it is difficult to acquire gallery samples for each person in all contexts. We discuss our approach in the light of Figure 2, which presents an overview of the system architecture during run time. Suppose the test data enters into the system. The first module i.e., 'Feature extraction module' will extract the soft-biometric (both anthropometric and gait features) associated to the subject.

For the design of context detector, we adopt the same methodology explained in (Nambiar et al., 2017a), i.e., by calculating the direction of a stable joint vector. Suppose the context of the test sample is represented as *i, (where* $1 \leq i \leq 5$*)*[3]. After knowing the viewpoint of the test sample, the approach of (Nambiar et al., 2017a) was to search for the gallery samples in the very same Context viz., $Context_i$ where the intra-class variation will be minimal due to the same viewpoint and noise level of the sensor in that particular view. However, if $Context_i$ lacks the data samples due to some reason, we can still enable the system to do the searching in the other views, in a process that we denote *cross-context analysis*. As per

[3]The dataset is already organized in five views with ranges (∼0°,∼30°,∼90°,∼130°,∼180°), so we map each angle to one of the views.

such an approach, we conduct searching across all the contexts to leverage all gallery samples. Finally, the matching scores from all contexts will be fused via score level fusion and given as the overall Re-ID score and based on that the Re-ID ranked list will be made.

We detail the internal structure of an individual context module in Figure3. Each contextual module is pre-trained according to the feature selection conducted for that particular context against all other contexts, including the same. In other words, it learns the set of relevant features in a particular gallery context, given the same/different context as the test context. Based on this analysis we learn feature set $S_{\text{i,l}}$ a priori, showing which are the features of interest in $Context_l$, given the test sample in $Context_i$. Feature selection among five contexts results in 25 possibilities (five feature subsets in each individual context).

A pictorial representation of the internal model of each individual context is presented in Figure 3. When the test context i is determined by the system, it will select the appropriate feature set $S_{\text{i,l}}$, for a particular context l. According to the feature selection conducted among different contexts as a part of the Cross-context analysis, feature subsets $\text{S}_{\text{i,l}}$ have been pre-trained.

$$S_{\text{i,l}} \in \{0,1\}^D \tag{4}$$

Then, the test feature vector (f) will carry out a multiplication with the selection vector $S_{\text{i,l}}$, so that only the relevant features will be chosen out of the whole set of D features. Similarly, selection of the relevant features were also carried out at the gallery as well, via multiplication of $S_{\text{i,l}}$ and Gallery feature vectors (f_{lmn}). Afterwards, the matching of the selected set of features in probe vs. gallery is carried out at a nearest neighbor classifier, and the matching score (C_{lmn}) is given as the output from the context module. Assuming that d is the index of the feature in a feature set, let's represent the overall feature matching (after selected feature multiplication) as follows:

$$C_{lmn}{}^{(d)}(f,i) = |f^{(d)} - f_{\text{lmn}}{}^{(d)}|.S_{\text{i,l}}{}^{(d)} \tag{5}$$

The score-level fusion brings the overall score of all the selected features in for a particular gallery feature vector:

$$C_{lmn}(f,i) = \sum_d C_{lmn}{}^{(d)}(f,i) \tag{6}$$

Then, the best matching score is computed by calculating the minimum matching score. Note here that the best score out of 3 gait cycles (minimum score per person) is selected as his individual score.

$$C_{ln}(f,i) = \min_m C_{lmn}(f,i) \tag{7}$$

Similar evaluation would have been conducted in each individual context. Then, at the score-level fusion module, all of such results obtained from each individual contexts will be fused according to the sum rule of score-level fusion(Ross et al., 2006):

$$C_n(f,i) = \sum_l C_{ln}(f,i) \tag{8}$$

Based on these scores computed for all persons in the dataset, the minimum matching score per person (maximum similarity) will be found out by estimating $n*$, the re-identified person ID, according to the following.

$$n^* = arg\min_n C_n(f,i) \tag{9}$$

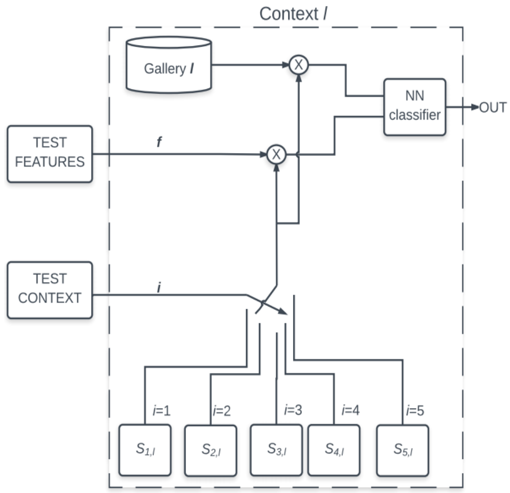


Figure 3: The internal architecture and functioning of an individual context is depicted above. Test features and the test context enters into the context module and the matching score will be given as the output. $\otimes$ refers to pointwise multiplication.

4 Experiments & Results

In this section, we explain various experiments carried out in order to understand the impact of cross-context analysis upon Re-ID framework, and the results obtained. For the analysis, we used publicly available *KS20 Vislab Multi-view Kinect Skeleton dataset*[4]. We first briefly explain the dataset. Afterwards, we explain the cross-context based system analysis, wherein we hypothesize the practical scenario of inadequate samples within the very same contexts of test and train. As a result, a naive strategy of searching space reduction by searching onto the very same context is not possible. Hence, in order to tackle it, we formulate a cross-context approach,

[4] `http://vislab.isr.ist.utl.pt/vislab_multiview_ks20/`

i.e., to search for the best match in all the contexts in order to exploit ample number of gallery samples, upon which we learn the relevant features apriori, via feature selection across various contexts.

Two experiments are conducted in this regard. First is the baseline case study where the contexts are defined by straight paths. For its verification, we used the straight line walkings acquired in the Vislab KS20 dataset. Here five various view directions are defined as contexts and hence cross-context analysis is carried out via feature selection (FS) learned among these five view-points. In the second experiment, we exploit subjects walking in circular paths, which implies that the contexts switch within each gait cycle. In that case also, we cross analyze each gait cycle with various contexts via feature selection.

4.1 Dataset

In this work, we exploited the Kinect$^{\text{TM}}$ based dataset proposed by the authors (Nambiar et al., 2017a) viz., *KS20 VisLab Multi-View Kinect skeleton dataset*, consisting of different view-points specifically designed towards view-point invariant long-term Re-ID. In particular, it consists of multi-view Kinect skeleton (KS) data sequences collected from 20 people, walking in five different directions *i.e.*, Left lateral (LL at $\sim 0°$), Left diagonal (LD at$\sim 30°$), Frontal (F at $\sim 90°$), Right diagonal (RD at $\sim 130°$) and Right lateral (RL at $\sim 180°$). Altogether, 300 skeleton video sequences (3 sequences per person along a direction) were collected. The five contexts $\mathbf{v_1}, ..., \mathbf{v_5}$ spread around their respective cluster means $\mu = [1.67, 35.63, 92.83, 130.70, 180.17]^{\top}$ degrees with standard deviations $\sigma = [3.64, 4.90, 3.29, 5.34, 3.99]^{\top}$ degrees.

4.2 Experiment 1: Walking along straight paths (Directional contexts)

As mentioned earlier, we first conducted a baseline study of directional contexts upon subjects walking along straight paths. Within the same study, we also assume yet another realistic constraint that not all the galleries contain equal number of samples. Due to this latter assumption, it is not possible for the system to reduce the search space to the very same context in search of the matching person (because, sometimes it may lack gallery samples), instead it has to search for a different context which has sufficient amount of training samples. This is the new paradigm we term as cross-context analysis. According to this, among various contexts, we learn a priori the relevant features via feature selection.

In order to better understand the proposed concept of cross-context analysis, we conducted three different case studies, by changing the degree of availability of gallery samples in contexts. (i) Five-cross-context case known as *Full cover gallery* (ii) Four-cross-context case known as *Sparse cover gallery* and (iii) One-cross-context case known as *Single cover gallery*.

- **Five-cross-context (Full cover gallery)** is the case where all contexts of every subject are represented in the gallery. Or in other words, we have the probe person available in all the five context galleries. Hence, the test sample is compared against all the remaining 299 data samples in all the five contexts except the test sample.
- **Four-cross-context (Sparse cover gallery)** is the case, where each subject is represented in other contexts but not exactly the same context of the test. In other words, we remove the test person from the same context and thus only the matching person data samples available in the gallery are from other four different contexts. Here, each test sample is compared against 297 data samples in the gallery except the case that the test subject is present in the very same context.
- **One-cross-context (Single cover gallery)** is the case where each subject appears only in a single context in the gallery, different from the probe *i.e.*, we remove the test person samples from all the contexts except a random context other than the probe context. Hence, the test sample is matched against 288 gallery samples, the case that the test subject is present in only one random context, other than the very same context.

Within each of the aforementioned cases, context unaware vs. context-aware matching techniques are performed. Within the former (context-unaware), (a) No FS and (b) Global FS are conducted. Method 'no FS' does not consider any Feature selection and thus the matching will be the basic feature matching of 74D feature vectors in all the gallery contexts. The second method (Global FS) conducts feature selection globally upon the whole set of data irrespective of the context. Feature matching will be carried out upon these globally selected set of features. On contrary to these context-unaware paradigm, we carried out context-aware case studies as well, where the notion of the context is taken into consideration as follows: (a) 1-context, (b) 2-context and (c) Cross-context. The first two cases assume equal gallery distribution among the contexts and hence works only for full cover case.[5] This was the baseline state-of-

[5]For sparse and single cover, the original proposal of

Table 1: Chart showing the Re-ID accuracy rates for Experiment 4.2.3. The accuracy rates shown in each cell represents Rank-1 CMC rate.

		Context-unaware		**Context-aware**		
		No FS	Global FS	1-context	2-contexts	Cross-context
Equal gallery samples	(i) Full cover (5 contexts)	74.67%	78.33%	88.00%	88.67%	82.33%
Data deficiency of samples	(ii) Sparse cover (4 contexts)	28.00%	41.67%	-	-	44.33%
	(iii) Single cover (1 context)	8.33%	12.67%	-	-	18.33%

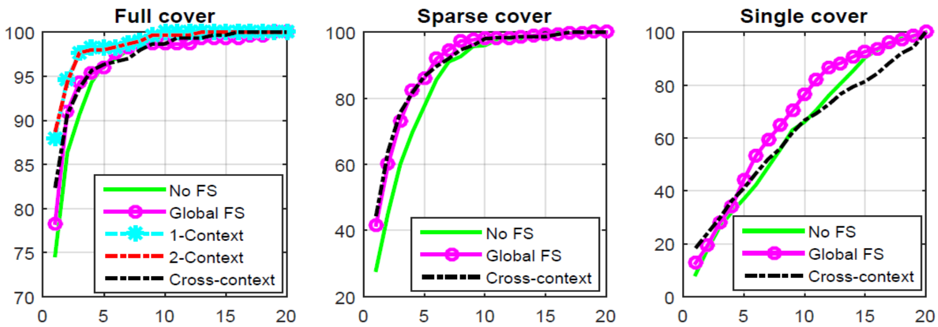


Figure 4: Cumulative Matching Characteristic curves for rates for Experiment 4.2.3. 1-Context and 2-Context scenarios of Context-aware cases are applicable only in Full cover case, where equal gallery samples are present.

the-art proposal in (Nambiar et al., 2017a). The last method viz., *Cross-contexts*, execute feature selection relying on the notion of context also by considering the incomplete gallery scenario.

The Cumulative Matching Characteristic curves and the Rank-1 Re-ID rates for the aforementioned cases are shown in Figure 4 and Table 1 respectively. The first observation drawn out is that the context-aware case outperforms context-unaware cases. The improvement in Re-ID performance by incorporating feature selection scheme as well as context framework is clearly observable. Within the context-unaware cases, we could observe that 'Global FS' improved the results compared to the 'no FS'.This clearly accentuates the significance of Feature selection in Re-ID performance. Second, by comparing the context-aware cases, we can observe that the best results are reported in the baseline 1-context/ 2-context scenarios, provided equal gallery samples are available (i.e., Full cover). Nevertheless, in practical scenarios of sparse/ single cover, they are not applicable.

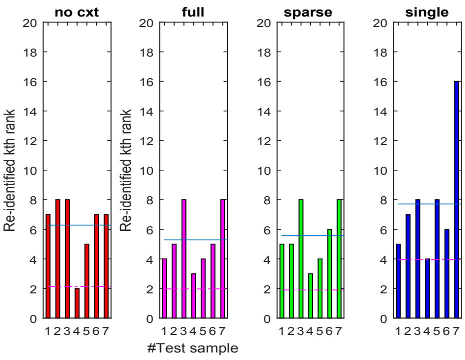
According to our new proposal of 'cross-context', we can observe that the rank 1 score of 'Cross-context' outperforms both 'no FS' and 'Global FS', in all the three gallery cover scenarios irrespective of the gallery size in each context. Although in the Full cover gallery case, this result is bit lower than the state-of-the-art (Nambiar et al., 2017a) result, in the other cases the results are highly promising and competitive with respect to the classical context-unaware cases, showing the impact of cross-context analysis in data deficiency practical situations. Thus, it is quite informative to note that when the relevant features are selected according the context by learning the feature selection across various contexts, the Re-ID performance can be improved. Since data deficiency in certain viewpoints are a big challenge in practical Re-ID circumstances, cross-context customized FS approach brings great significance into the paradigm.

The best Re-ID performance among the three gallery settings was observed in the Full-cover gallery context. This could be ascribed to the fact that there are more and better examples to match to the test sample. Sparse cover produces worse results compared to the former since there is no availability in the very same context, instead it searches and finds the best matching in four other different contexts. The worst case is the Single cover scenario, where only a single cover gallery (other than the test context) is provided, where always the matching is poor in terms of the number of samples and quality of data, but still outperforms the context-unaware case.

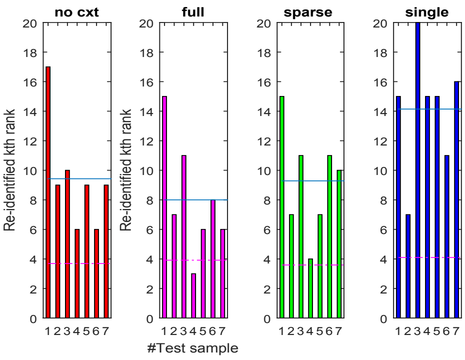
4.3 Experiment 2: Walking in circular paths (Switching of Contexts)

We conducted another experiment as well, based on the cross-context analysis. In this second case, we experimented the complicated scenario of context switching, which is basically change of view-points

(Nambiar et al., 2017a) will not work due to the data deficiency issue.



(a) Person#1



(b) Person#2

Figure 5: A case study of "switching the context", carried out upon two persons is depicted above. In each row, diagrams result from cross-contextual analysis (incomplete gallery samples) in the order of *no context, full, sparse* and *single cross-context* respectively. The mean and standard deviation in each case is marked via the blue straight line and magenta dash-dot line respectively. The best results are associated with lower mean k-Rank.

within a gait cycle itself. As a simple instance of such a situation for our experiment, we used circular path walkings of a subset of people who also have been a part of the original Vislab *KS20* dataset. For this pilot study, we leveraged two people's circular walking sequences from the dataset.

Since the circular sequences of KS20 datasets were acquired after a gap of one year, they clearly ensured a long term Re-ID scenario, with drastic variations in view-point. The circular walkings of two people are used as the test sequences, and then matched against the linear training sequences of KS20 dataset [6].

The results of the Re-ID performance of switching contexts incomplete gallery scenario via cross-context are analysed in this experiment. Figure 5(a) refers to the experimental results of Person #1 and Figure 5(b) refers to the experimental results of Person #2. For a particular person, seven samples have been obtained. Hence, we analyse the k-th rank at which each sample of the person is correctly re-identified (represented with individual bars). The mean (blue straight line) and standard deviation(magenta dash-dot line) are also depicted in the bar graph. Lower the rank, better the performance.

We computed the Re-ID performances of context-unaware scenario('*no_cxt*') (*Context-unaware*) vs. full, sparse and single (*Context-aware*) scenarios. '*no_cxt*' scenario is the case where no notion of context was incorporated, so that the system performs as if the classical Re-ID models (with no splitting of the data in the gallery). Among all the context-aware Re-ID results, we can observe that the Re-ID performance is in the descending order of Full, Sparse, and Single respectively among the context-aware cases. The gradual reduction in the performance is found to be in accordance with the reduction in the number of samples in the gallery. Hence, it clearly accentuates the necessity for adequate number of training samples in the gallery set. Regarding '*no_cxt*' scenario, it was found to be underperforming compared to the full cover case, which clearly underlines the significance of the notion of context.

Person#1 and #2 are a woman and a man, respectively. Considering the relative population of women and men in the dataset (16 men and 4 ladies), the overall Re-ID performance was found to be with lower k-th rank Re-ID for Person#1, meaning that Re-ID of the lady candidate was much easily done compared to the man candidate.

5 Conclusions

In this work, we presented a novel method called 'Cross-context ensemble fusion framework'- a context-aware person Re-ID method- for re-identifying people in a long term video surveillance system. The key proposals of the architecture is to facilitate cross-context analysis via feature selection carried out across various contexts, and thus trying to bypass the real-time Re-ID challenge of insufficient data samples. In this regard, detailed analysis in terms of different case studies viz., full, sparse and single cover gallery were carried out. From the results, it was observed that full gallery case performs the best among the group, highlighting the importance of large amount of training samples in Re-ID matching. How-

[6] Regarding the circular path data, a full circle contains five or six gait cycles, out of which only half of them were considered, wherein the person walks towards the camera (training set contains sequences towards the camera). Thus, altogether seven gait cycles are extracted out of whole sequences of walking.

ever, in many practical cases the full gallery case is not-available. In these cases we have shown the applicability of the proposed cross-context analysis and the advantages over the no-context case.

As a part of this study we carried out another practical scenario of 'Switching of contexts' in incomplete gallery samples, with the help of circular walking examples. Among the observations, we could again observe the precedence of full cover case. However, in both experiments, context-aware case outperformed context-unaware case. Despite our tests consider view-point as the contextual feature, we believe the method can be useful for the cross-context analysis of other contextual features that are inherently pose invariant but suffer from heteroscedastic noise sources, for instance distance, clutter or velocity. In future, we also envisage to learn contexts automatically (e.g., data clustering technique).

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