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Video De-Identification

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Abstract:
Person identification based on biometric method has been broadly studied in the last two decades, while information appearing in different actions like bend has been recently acted to this end. Such that in most applications it is sufficient to recognize the performed activity, whereas the ID of persons performing performance is not an important aspect. Since the same human body representations, e.g., body silhouettes, can be employed for both tasks. it is need to create privacy preserving representations automatically . We have applied 2D Gaussian filtering to unclear the human body silhouettes that gives information about the person ID. It is done experimentally showed that how the use of filtering affects the person identification and action recognition performances in different camera set-ups formed by an arbitrary number of cameras. In addition, the discriminative ability of different activities is examined to detect cases in which it is possible to apply Gaussian filter with a greatest variance.

Keywords: de-identification of human body silhouette, action recognition, Gaussian filter

I. INTRODUCTION

An increasing number of video cameras observe public spaces, like streets, airports, railway and bus stations, shops, schools and other educational institutions. In some use-case scenarios, like video surveillance, there are justified reasons for capturing and sharing acquired multimedia data to authorize personnel, due to security reasons. In most scenarios it is sufficient to detect the activity, whereas data on persons engaged in these activities do not matter. Therefore, there is a strong need for protecting the privacy of persons captured in such multimedia content. The process of oncealing identifying the ID of a person appearing in a given set of data, referred as persons de-identification, should be done. Since the performed activities may be of particular interest, the goal in this query is to protect the privacy of individuals without compromising on the performed activities and other contextual content. Identification is a process opposite to the de-identification, with the use of all possible features such as face, silhouette, and biometric and body posture to identify person. In order to obscure such features to prevent identification, appropriate computer vision method should be devised. Humans usually identify persons by observing their faces, it is not surprising the fact that the majority of de-identification methods deal with face de-identification. Proposed methods can be categorized into two groups: the ones exploiting image distortion algorithms and those employing the k-Same family algorithms. Exploiting image distortion algorithms alter the facial image regions using data suppression techniques (e.g., by covering part of the face), or some kind of obfuscation, such as blurring or pixilation (i.e.,imagesub-sampling). Implementation of the k-Same algorithm replaces the face of the person under consideration with a-priori known one belonging to a set of k generic faces. In Various approaches we find de-identification of the whole human body, instead of just the face, taking into account that gait recognition has been mostly used to identify persons at a distance in security applications. The complete human body is masked using various types of blur functions. Persons on a street scene are replaced by other (a-priori known) persons appearing in a training set of images containing similar scenes. The other way to manipulate the human body regions of an image is to replace them with background.

II. PERSON IDENTIFICATION PIPELINE

A. *Preprocessing Phase*

Elementary videos depicting one activity instance (a single movement period) are manually created by splitting multi-period videos. Elementary videos are used for training. Elementary or multi-period videos can be used in the test phase. The number of frames in elementary videos may vary for different activity types. Activity instances may vary in certain period. even different instances of the same activity type performed by the same person may vary in duration. By applying proper video frame segmentation techniques, like background subtraction, or chroma keying, human body silhouettes are detected in video frames and binary images (masks) encompassing the human body Region Of Interest (ROI) are determined. The below figure shows an example video frame of the i3DPost database depicting an instance of walking activity, the corresponding human body ROI and mask.

Figure.1. Posture images depicting five activities observed from various viewing angles. From left to right: walk, run, jump in place, jump forward, and wave one hand.

The resulting binary posture images are vectorized column-wise, in order to produce the so-called posture vectors.

B. Video Representation and Classification

In the training phase, posture vectors are obtained by applying the prescribed process on the training videos are clustered using the k-means algorithm in order to produce action-independent posture vector prototypes, so called dynemes. Dynemes preserve human body shape, observation angle and activity information. After dynemes calculation, posture vectors of training and test videos can be represented in the dyeneme space by applying fuzzy vector quantization. Training and test videos are finally represented by the action vectors, which are the mean vector of the corresponding posture vectors, represented in the dyneme space. The shape of human body silhouettes is crucial for person identification in the described framework; it has to be modified to prevent person identification from activities. We will modify the color (RGB) values of the video frame pixels corresponding to the human body. In order to perform this in a structured way and not to introduce artifacts on the resulted video frame. a zero-mean, discrete two-dimensional Gaussian filter of size h, defined by:

$$h_g(n_1, n_2) = e^{-\left(n_1^2+n_2^2\right)/2\sigma^2}$$

$$h(n_1, n_2) = \frac{h_g(n_1, n_2)}{\sum_{n_1}\sum_{n_2} h_g}$$

Where n_1 and n_2 denote the indices in the filter window of size h and σ is the standard deviation of the Gaussian distribution.

Gaussian filter replaces each pixel in the ROI with a weighted average of the neighboring pixels such that the weight given to a neighbor decreases monotonically with respect to its lateral distance from the central pixel. In this way the effect of distortion is applied locally, which is useful for keeping the key information relating to the performed activity. By changing the filter parameters, i.e., the value of σ, the effect of the distortion can be appropriately adjusted. The degree of blurring of a Gaussian filter is parameterized by σ, and the relationship between σ and the degree of smoothing is proportional. A larger σ value implies a larger smoothing and excessive blur of the image features. To determine the appropriate filer size h and adjust the degree of blurring, we have experimented with different filter sizes (h values ranging from 3 to 25 pixels) and with Gaussian distributions of different standard deviation (σ values ranging from 3 to 10). Different h and σ values influence shape of the extracted human body silhouettes and, thus, the action recognition and person identification performance. Since we are focused on lowering the person identification performance, while keeping the action recognition performance high, we have chosen the values providing the maximal p_a/p_I ratio, where p_a, p_I denote the obtained action recognition and person identification rates, respectively.

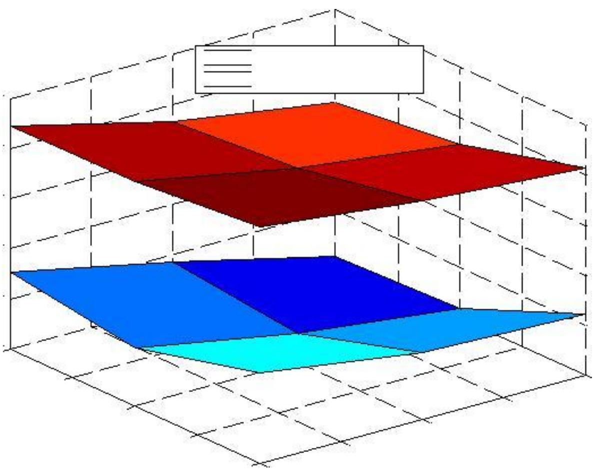


Figure.2.identification rates, respectively

After applying the above described process, we have experimentally chosen the values of h=20 and σ=6.4. The corresponding Gaussian filter is shown in below figure

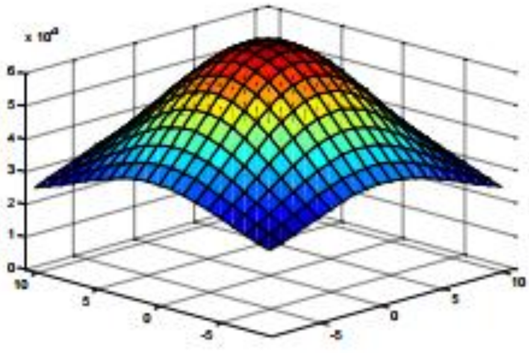
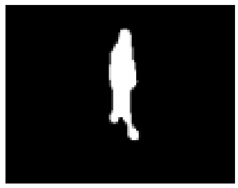


Figure.3. corresponding Gaussian

Since 2-dimensional Gaussian functions are rotationally symmetric, the amount of blurring performed by the filter will be the same in all directions. This property implies that a Gaussian filter will not bias subsequent edge detection in any particular direction and that edges in the resulted image will not be oriented in some particular direction that is known in advance. We apply the Gaussian filter to image ROIs centered to the human body ROI and having size equal to s times the size of the human body ROI. We have experimentally found that a value of s=1.1 gives the best results with respect to our goal. Fig. 5 shows example video frames and the corresponding human body silhouettes for actions walking and jumping in place after applying the Gaussian filter using the value *s*=1.1. As can be seen in this Figure, the human body silhouettes obtained by using the blurred video frames are coarser, compared to the ones obtained by using the original video frame. This will affect the person identification performance. In addition, it can be seen that the global action information, e.g., opened legs for the case of walking, is preserved. Thus, action recognition performance should not be affected so much.

Frame with a blurred Expanded ROI **mask of a blurred ROI**



Frame with a blurred Expanded ROI **mask of a blurred ROI**

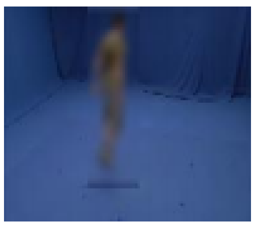


Figure.4.action recognition performance

V.CONCLUSION

We have proposed a pipeline for person de-identification based on activities. We have employed Gaussian blurring in order to change the obtained human body silhouettes, so as to discard identity information, while preserving action information. To improve the de-identification results, the discriminative ability of different observation angles and of specific activities can also be taken into account in order to apply additional blurring steps.

VI. REFERENCES

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