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Enhance the systems ability to perform under varying lighting conditions, angles, and occlusions

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Abstract

For the purpose of automated face recognition, a method is suggested that combines gait, a behavioural biometric, with the face, a physical biometric. The unknown person's identity is determined using a decision-level fusion technique, where the gait classifier receives the top matches from the face classifier. Using data acquired from an optoelectronic motion capture system, a new system is developed for gait identification. This system makes use of a number of gait parameters that have been shown to be the most important for recognition. It is also feasible to identify someone without using their face, fingerprints, palm prints, knuckles, ears, or iris. Gait analysis allows for the recognition of a person even when the individual is not aware of it. Finding a person's gait characteristics is the goal of this study, which employs a CNN model, a deep learning algorithm. Python was the language of choice for the investigator as they built the foundational architecture of the deep learning CNN. The investigator's job is made easier by importing the default library packages in keras, an open-source neural network library designed in Python that operates on Tensorflow. The database is fine-tuned using industry-standard techniques such as grouping technic, systematic random picture removal, Laplacian fuzzy image removal, and contour broken image removal. Substituting a mix of the softmax and sparsemax functions for the softmax function in the last layer of the deep learning CNN considerably improves it.

Keywords: Biometric, Face Recognition, Network, Python, Face, Fingerprints

1. Introduction

A person's personal information is closely related to their identify. The demand for personal identification is increasing in today's rapidly developing world. It is possible to make a prediction both with and without the target's awareness. Fingerprint, iris, face detection, and palm print are the usual tools for human identification. These days, people additionally use their tongues, knuckles, walking patterns, and general characteristics to aid in detection. A person's genetic makeup, electrocardiogram (ECG), heart rate, and other biometric data are used to determine their precise identification. When it comes to criminal cases and attendance purposes, methods such as biometric detection, facial perception, forensic identification, and face detection are used to identify the individual.

Gait analysis may identify a person even when they are unaware of it. Modern technology allows for easier and more precise person classification at lower cost using local devices. To keep an eye out for criminal activity, video surveillance cameras have been set up in homes, businesses, and public spaces. Identifying individuals is possible using the footage captured by these cameras. When it comes to picking up new skills, artificial intelligence is king. Without any prior information about the individual, deep learning-a kind of machine learning-is used to determine their identity. Training a system to learn on its own is preferable than hard-coding its behaviour.

Without their awareness, this individual can be predicted thanks to this study. The researcher favoured using gait analysis and deep learning convolutional neural networks to do the investigation.

2. Motivation

In order to ensure the safety and security of individuals, video surveillance systems are installed in homes, businesses, and public spaces. The globe is now equipped with a vast network of video surveillance cameras and closed-circuit television (CCTV) systems. Such footage has recently shown promise as a weapon in the fight against terrorism. Keeping an eye on all of these films has been a huge burden for the staff. In general, it requires a lot of focus to watch movies and give it data for later usage.

The video does show the incident, but both the police and the general public have found it very difficult to positively identify the perpetrator. Methods for manually identifying a suspect in a crime might vary according on the available evidence and the amount of time available.

The fact that attendance is a subtle kind of identification is another perk. Biometric or swiping systems are often used to track employee attendance. There are occasions when there is a large line to enter attendance, and at such times, the transmission of illness might be facilitated by using biometric machines. An alternative method of recording a person's arrival and departure times for use in a database should be implemented.

We need a new system to solve the problems of identifying criminals and keeping track of attendance without biometrics or long lines. Problems like this may be resolved by gait analysis that makes use of deep learning techniques. This aids in teaching the system to recognise an individual and act accordingly.

3. Review of Literature

As a sparse linear combination of training samples using L^1-norm minimum, sparse representation-based classification (SRC), demonstrated that the input test picture significantly improved facial recognition (FR). By including an identity occlusion dictionary into the coding process, SRC has the potential to provide favourable FR results when dealing with face occlusion in images. Nevertheless, the computational cost of reducing the L^1 norm and the SRC scheme's huge atomic number is high. In this study, we show how to implement a GRRC, or Gabor robust representation and classification system, that uses the Gabor function to provide trustworthy FR. In addition to improving face discrimination, using Gabor features enables the construction of an occlusion dictionary using significantly fewer atoms than identities. Also, it shows that the L^2-norm may help regularise the coefficients in the L^1 norm after transforming the Gabor function, which drastically cuts down on the processing cost of occluded face pictures for coding.

According to research by Jozer et al. [2023], facial features are often used in biometric security systems for identification purposes. Because it is possible to remotely collect facial biometrics even in the absence of detection of physical touch, this kind of biometrics is considered acceptable. There is no need for the customer to cooperate in order to be identified or validated. All sorts of uses benefit from human-faced recognition systems due to their merits. Accurate dependability of identification is therefore the primary objective, although it is difficult to accomplish in practice. Despite the abundance of ideas, only few have found practical application. Even with the advent of improved face recognition algorithms, problems with noise from utilised cameras, and imperfect imaging, occlusions and lighting still play a role in the scenario. To fix these issues, we need HBB-Next, or Next Generation Hybrid Broadband. The project also includes working on the foundation for the multimodal interface that interacts with the HBB-TV user. This provided an opportunity to compare and contrast various kernel approaches with more conventional face-recovery techniques.

4. Objectives of the study

1. Enhance the systems ability to perform under varying lighting conditions, angles, and occlusions.
2. Develop algorithms to handle variations in walking speeds, postures, and facial expressions.

5. Research Methodology

Well standardized bench marking CASIA dataset B and CASIA dataset C are available in internet, as open access is taken and used from the site http://www.cbsr.ia.ac.cn/english/Gait%20Databases.asp for training and testing the convolutional neural network. Two different datasets captured in day time and in night time are used to train the images.

Dataset B consists of 124 person silhouettes with 11 views including various angles, clothing and accessories. It is a large multi view dataset for gait process. It is captured during the day light with normal video camera set at various degrees of angles to capture the walking styles simultaneously.

Dataset C consists of 153 person silhouettes with various walking conditions like normal walking with and without bags, slow walking and fast walking. The videos are collected during night time with infra-red thermal camera. It is a standard, well refined and validated database collected during 2005 and currently used for research purpose for finding gait features and other gait analysis.

To begin person classification, the video must be transformed into a silhouette. It takes almost a thousand silhouettes to transform a 12-second video. While 32% are utilised for testing, 68% are used for silhouette training on this exam.

It is not possible to feed the neural network a full dataset all at once. Consequently, the datasets are organised into batches. Epoch stands for the dataset's forecast. For instance, with a batch size of 20 and a data set containing 1000 photos, the epoch should execute 50 iterations. Classification is then applied to CASIA datasets B and C. Colour, size, and form are used to evaluate each image's size, and if necessary, they are converted to greyscale.

6. Results and data Interpretation

6.1 Tests with spatio-temporal parameters

The recognition potential of the spatio-temporal parameters was studied by running the gait classifier using these parameters individually. The results are depicted in Table 1. The combination of all these parameters and various combinations of the parameters with the highest recognition rates were then taken. The results are shown in Table 2.

The following observations can be made based on these results:

The recognition rates based on individual parameters are lower than those based on the combination of all the parameters.

Table 1: Gait Classifier Recognition Rates Using Spatio-Temporal Parameters

Gallery Size	Stride length	Stride time	Step length	Step time	Step width	Cadence	Walking speed	Stance phase time	Swing phase time
24	25.00%	25.00%	29.17%	62.50%	12.50%	58.33%	20.83%	29.17%	20.83%
156	2.56%	7.69%	5.77%	28.21%	2.56%	27.56%	1.92%	15.38%	8.33%

Table 2: Gait Classifier Recognition Rates Using Various Combinations Of Spatio-Temporal Parameters

Gallery Size	All spatio- temporal parameters	Step time + cadence	Step time + cadence + stance phase time
24	79.17%	58.33%	66.67%
156	47.44%	30.77%	35.90%

- When the two best-forming parameters (i.e., step time and cadence) are combined, the recognition rates are better than those based on individual parameters but worse than those based on the combination of all the parameters.
- When the three best-performing parameters (i.e., step time, cadence, and stance phase time) are combined, the recognition rates are better than for the above combination but worse than those based on the combination of all the parameters.
- The above observations indicate that the low-performing parameters are contributing discriminatory information which complements that contributed by the higher-performing variables.

6.2 Comparison with previous results
The above observations are consistent with the results obtained previously with a smaller gallery of 24 subjects, except for the following: The recognition rates for the combination of the two best-performing parameters are better (rather than worse) than those based on the individual parameters.

The overall recognition rates for the larger gallery size of 156 subjects are less than those for the smaller gallery size of 24 subjects for these tests (this will continue to hold true for subsequent tests, described in the subsections following this one). However, it should be pointed out that this decrease in performance with an increase in gallery size is in accordance with what was observed in previous tests with 24 or fewer individuals.

6.3 Tests with angle trajectories
The recognition potential of the angle trajectory parameters was studied by running the gait classifier using these parameters individually. The results are depicted in Table 3. The recognition rates obtained by taking various combinations of these parameters are shown in Table 4.

The following observations can be made based on these results:

1. The recognition rate based on the combination of all the parameters is worse than the rates based on some of the individual parameters. This is not surprising since a combination of a large number of parameters is being taken, many of which are not yielding good results individually, and the discriminatory potential of the better- performing variables is nullified by the several low-performing ones.
2. Component 3 of the right hip angle trajectory is the best performing variable overall, yielding a recognition rate of 89.1%.
3. When only the lower body angles are combined, the recognition rate is worse than that obtained for the combination of all parameters (87.82% v. 90.38%).

Table 3: Gait Classifier Recognition Rates Using Lower Body Angle Trajectories

Gallery Size	Pelvis Angles			Left Foot Progress Angles			Right Foot Progress Angles			Left Hip Angles		
	1	2	3	1	2	3	1	2	3	1	2	3
24	75.00%	87.50%	70.83%	62.50%	91.67%	79.17%	41.67%	91.67%	58.33%	79.17%	91.67%	95.83%
156	37.18%	62.82%	19.23%	33.33%	63.46%	46.15%	24.36%	58.97%	29.49%	49.36%	62.18%	77.56%

Gallery Size	Right Hip Angles			Left Knee Angles			Right Knee Angles			Left Ankle Angles			Right Ankle Angles		
	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
24	75.00%	95.83%	100%	87.50%	95.83%	95.83%	62.50%	95.83%	91.67%	91.67%	95.83%	87.50%	79.17%	87.50%	91.67%
156	50.64%	76.28%	89.10%	63.46%	83.33%	73.08%	33.33%	73.72%	78.21%	58.97%	82.69%	62.82%	41.67%	71.79%	67.31%

Table 4: Gait Classifier Recognition Rates Using Upper Body Angle Trajectories

Gallery Size	Thorax Angles			Neck Angles			Spine Angles		
	1	2	3	1	2	3	1	2	3
24	62.50%	50.00%	58.33%	20.83%	37.50%	25.00%	58.33%	75.00%	54.17%
156	20.51%	27.56%	26.28%	5.77%	8.33%	6.41%	32.69%	41.03%	26.28%

Gallery Size	Left Shoulder Angles			Right Shoulder Angles			Left Elbow Angles			Right Elbow Angles		
	1	2	3	1	2	3	1	2	3	1	2	3
24	62.50%	83.33%	66.67%	66.67%	79.17%	66.67%	70.83%	-	-	58.33%	-	-
156	26.92%	37.18%	40.38%	31.41%	29.49%	33.97%	36.54%	-	-	29.49%	-	-

7. Conclusion

The system used a model-based approach to fuse the face and gait, instead of a holistic one based on silhouettes. It forms the gait signature using dynamic gait features, such as spatio-temporal variables and joint angle trajectories. It also made use of the gait and a facial recognition method based on Bayesian inference.

Some of the findings from the empirical evaluation of this system are outlined below:

While both spatial-temporal variables and angle trajectories were beneficial for recognition, the latter produced better recognition rates overall.

- The best-performing spatio-temporal variables were step time and cadence, whereas the best-performing angle trajectories were hip angle trajectories.
- The upper body angle trajectories did not perform as well as the lower body ones, including the ones for the ankles, knees, hips, foot progression, and pelvis.
- The aggregate recognition rates were much greater than those of the individual angles when trajectories with low recognition rates were used.

For multiple sets of gait variables, the integrated face-gait classifiers performed better than their constituent parts. This shows that gait can be used to augment face in situations where high resolution face data is unavailable, and the face classifier alone does not perform well. These tests were redone using a bigger dataset that included both the original 24 participants and 132 "synthetic" participants (whose gaits were created from the original 24 participants'). While the majority of the earlier findings held true when comparing this larger data set to the earlier one, it did reveal that specific gait variables, like the spatio-temporal variables, became less useful for recognition as the sample size grew larger. Nevertheless, across various combinations of gait characteristics, the integrated face-gait system maintained superior performance compared to its constituent parts, proving the approach's potential even with bigger datasets.

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