Deep learning for law enforcement: a survey about three application domains

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Abstract

Deep learning is rapidly growing, obtaining groundbreaking results in speech recognition, image processing, pattern recognition, and many other application domains. Following the success of deep learning, many automatic data analysis techniques are becoming common also in law enforcement agencies. To this end, we present a survey about the potential impact of deep learning on three application domains, peculiar to law enforcement agencies. Specifically, we analyze the findings about deep learning for Face Recognition, Fingerprint Recognition, and Violence Detection. In fact, combining 1) data from the routine procedure of collecting a subject frontal and profile pictures and her/his fingerprints, 2) the pervasiveness of surveillance cameras, and 3) the capability of learning from a huge amount of data, might support the next steps in crime prevention.

Keywords

Face Recognition, Fingerprint Identification, Fingerprint Verification, Violence Detection, Deep Learning, Artificial Intelligence, Law Enforcement

1. Introduction

From its dawn as a discipline, Artificial Intelligence (AI) aims to understand if we are able to implement machines with the ability to think. During this unceasing exploration, symbolic AI, also known as Good Old-Fashioned AI [1], tries to model the knowledge of the application domains in a high-level human readable formalism. As such, countless applications relies on symbolic AI, ranging from personal health systems [2, 3] to police investigations [4], to the modeling of automata [5] and autonomous agents [6, 7, 8], to smart home reasoning systems [9, 10, 11] and many more. On the other side, machine learning tries to give to machines the capability of autonomously learning from examples. In this regard, we are witnessing the rapid growth of deep learning: it aims to build computational models, composed of multiple processing layers, able to autonomously learn the best representations of data to accomplish specific tasks, such as speech recognition, visual object recognition, pattern recognition, and many others [12].

Following the progress achieved by AI, several data analysis method based on symbolic AI and/or deep learning are becoming popular among law enforcement agencies [13]. To this end, we present a survey about the impact of deep learning techniques on three application domains, which are common to

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law enforcement agencies:

- Face Recognition, in connection to the use of mugshots gathered during the routine procedure of collecting a person frontal and profile pictures, her/his fingerprints, and personal information;
- Fingerprint Recognition and, specifically, the extraction of minutiae, i.e. the distinctive features used for fingerprint matching;
- Violence Detection, with the goal of unburdening law authorities from the need to manually check hours of video footages to identify short events.

While these domains seem different, the computerization of the related tasks has common roots in Computer Vision and is rapidly evolving thanks to deep learning. Therefore, the goal of this paper is to give a concise description of such evolution, showing the potential impact of deep learning in security applications and crime prevention.

The rest of the paper is divided into sections dedicated to each application domain, i.e. Face Recognition (Section 2), Fingerprint Recognition (Section 3), and Violence Detection (Section 4). Finally, Section 5 draws the conclusions of this survey, highlighting some aspects which we consider worth of further research.

2. Deep Learning and Face Recognition

National police forces routinely collect two pictures (commonly known as mugshots), fingerprints, and personal information of a subject, for various purposes, ranging from releasing documents to registering criminals. Hence, there is a clear connection between Face Recognition and this data collection procedure, for what concerns the face identification. In fact, Face Recognition is one of the most natural biometric technique used for identification [14]. It has a significant advantage over other biometric techniques: it can be done passively, i.e. without explicit actions by the subject to be identified [15]. Therefore, due to the wide range of possible security applications, Face Recognition attracted the interest of the Computer Vision community for more than 40 years.

Thus, early approaches on Face Recognition were based on pure Computer Vision methodologies. Turk and Pentland [16] proposed Eigenfaces, i.e. the application of the Principal Component Analysis (PCA) to extract a vector of features that maximize the variance in a set of training images. By projecting a face image in the space obtained with the PCA, face identification can be performed with a nearest neighbor method, computing the distance from training images. While Eigenfaces maximizes the inter-class variance between face images of different subjects, it does not take into account the intra-class variance between the face images of a single subject. Instead, the Fisherfaces method [17] adds to the PCA the Linear Discriminant Analysis (LDA), in order to minimize intra-class variance. Differently from Eigengaces and Fisherfaces, Ahonen et al. [18] proposed to compute Local Binary Patterns Histograms (LBPH) on face images, dividing it into region to compute Local Binary Patterns (LBP). Similarly to Eigenfaces and Fisherfaces, a distance function based on LBPHs can be used to perform the face identification.

While these techniques (and those derived) obtained a good accuracy on datasets where some parameters such as pose, lighting, and expression are fixed, they are insufficient to extract stable identity feature invariant to real-world changes [19], such as in images got from videos and surveillance cameras. Therefore, they are not suitable in law enforcement, when comparing the two mugshots (a frontal and a profile pictures) collected by police agencies in ideal conditions, with images got in the wild. On the contrary, deep learning-based techniques demonstrated capable of extracting features that are invariant to changing conditions about facial expression, lighting, and pose. While there are some early methods which combined multiple Neural Networks and Belief Revision [20, 21] before the deep learning popularity, Convolutional Neural Networks (CNNs) significantly improved the accuracy in Face Recognition under unconstrained conditions. To this end, Taigam et al. [22] presented DeepFace, a 8-layer CNN to process 3-channels 152x152 face images, capable of getting a 97.35% accuracy on the Labeled Faces in the Wild (LFW) dataset [23]. Similarly, Schroff et al. [24] proposed Facenet, a 22-layer CNN trained in several experiments with a varying number of face images, between 100 and 200 million, belonging to 8 million of different subjects. They got 99.63% accuracy on LFW, using 220 x 220 input images. Cao et al. [25] showed the effectiveness of the ResNet-50 [26], a 50-layer CNN based on residual learning able to get a top-1 identification error of 3.9% on the VGGFace2 datset (composed by over 3 million of images of more than 9 thousands subjects).

The listed CNN-based techniques for Face Recognition are just few examples among the many which demonstrated they robustness to changing conditions and unconstrained face images (see Guo and Zhang [27] for a detailed list of deep learning-based Face Recognition techniques). However, to the best of our knowledge, there is a lack of research in understanding to which extent such techniques are effective in identifying a known subject when only the two standard images of police databases are available as training samples.

3. Deep Learning and Fingerprint Recognition

The patterns created by the epidermal ridges and furrows on our fingers, i.e. fingerprints, have been used for identification for more than 2000 years [28]. As fingerprints are a so discriminative biometric characteristic, the implementation of Automated Fingerprint Identification Systems (AFIS) has been a prominent topic in Computer Vision in the last four decades. Specifically, fingerprint matching to identify or verify a person's identity is based on the presence of singularities of epidermal ridges called minutiae [29]. In this regard, algorithms to extract features and perform matching on fingerprint images focused on two basic types of minutiae: bifurcations and terminations, i.e. the points where a ridge splits itself into two ridges and where a ridge ends [30, 31, 32]. In addition to issues such as image noise, distortions, rotations, and displacement, large variability in different impressions of the same finger and similarity between two images from different fingers make fingerprint matching a very challenging problem [33].

Traditional Computer Vision-based algorithms demonstrated their effectiveness on fingerprint matching, and specifically, on minutiae matching, evolving over the years. For example, in 1997, Maio and Maltoni [30] proposed to perform ridge line following on gray scale fingerprint images to identify terminations and bifurcations. Farina et al. [31] proposed to identify minutiae from skeletonized binary images. Fronthaler et al. [32] exploited symmetry features (linear and parabolic) to reduce noise and extract minutiae on grayscale images. Cappelli et al. [34] proposed a new representation for minutiae, treating the minutiae extraction and the fingerprint recognition as a 3D pattern matching problem instead of a 2D one, obtaining top-level accuracy results.

Of course, these are just few examples of the many algorithms and techniques available in fingerprint matching. In fact, as highlighted in the survey of Peralta et al. [33], even if the best performing algorithms are different, they are based on common features such as minutiae coordinates, angle, and type. Which is, then, the role of deep learning in fingerprint recognition, given the maturity of the field and the good performance of traditional Computer Vision-based algorithms? In recent years, deep learning-based techniques have been proven useful to overcome some of the limitations of traditional techniques. While traditional algorithms, such as those presented, perform well on rolled and plan fingerprints collected with dedicated sensors, they failed on latent fingerprints, i.e. partial fingerprints unintentionally impressed on surfaces [35, 36, 37, 38]. To this end, Tang et al. [36], proposed to convert the traditional operations for minutiae extraction into a CNN that can be trained end-to-end. Similarly, Cao et al. [38] presented a latent fingerprint recognition system based on CNNs. Li et al. [37] also proposed a CNN-based architecture, but with a different objective: enhance latent fingerprint images to be used for the fingerprint matching (performed with other applications).

Latent and partial fingerprint recognition is not the only open challenge addressed with deep learning in the field. In the use of fingerprints for authentication, Lin and Kumar [39] presented a model based on CNN to learn discriminative 3D representations of fingerprints in contactless fingerprint recognition applications. With the availability of high resolution scanners, CNN-based architectures have been developed to recognize sweat pores in high resolution fingerprints [40, 41]. Finally, deep learning techniques are being investigated to detect malicious attempt to authenticate via artificial fingerprints, for the development of anti-spoofing methods [42, 43].

4. Deep Learning and Violence Detection

The increasing availability of technologies for video-surveillance, combined to the need of unburdening authorities from the task of checking hours of video recordings, boosted the attention of the research community towards the automatic detection of violence in videos. The violence and fight detection is considered a task of human action recognition: specifically, it is a binary problem which consists of recognizing the presence or the absence of violence [44].

As violence detection is rooted in action recognition, the early works are based on Computer Vision techniques originally implemented for action recognition and can be categorized into two classes [45], using handcrafted features to represent actions:

- in local features-based techniques, the representation of an action is computed by using Points of Interest (POIs) across the frames of a video;
- in global features-based techniques, the representation of an action is computed by evaluating characteristics from multiple frames as a whole.

Among the techniques which are based on local features, Chen and Hauptmann [46] proposed MoSIFT, a technique that combines the Scale-Invariant Feature Transform (SIFT) [47] with optical flow to represent the movement of POIs. Xu et al. [45] evolved the use of MoSIFT by combining it with a non-parametric Kernel Density Estimation (KDE) to remove redundant and irrelevant features. They achieved good results on detecting person-to-person fights on videos, using sparse coding to represent the extracted features. Instead, Deniz et al. [48] proposed to compute acceleration from the power spectrum of adiacent frames to detect a large variation of speed, obtaining results comparable to MoSIFT, but with a faster algorithm.

Concerning the techniques based on global features, Hassner et al. [49] proposed the computation of the Violence Flows (VIF) descriptors, an evolution of optical flow which computes the changes in the magnitude of flow vectors, obtaining promising results on the detection of violence in crowds. Gao et al. [50] added to the VIF the orientation of the flow vector, proposing OVIF, improving the performance on the detection of person-to-person fights, but with a lower accuracy on crowd violence.

Deep learning contributed to advance the violence detection field by overcoming some of the limitations of the optical flow, such as discontinuities and camera motion, and by getting very good performance in person-to-person fights and crowd violence with the same model. Specifically, 3D CNN have been proven capable in learning spatio-temporal information, i.e. features which represent the motion information in a video, in addition to the spatial information in a single frame. For example, Ding et al. [51] presented a 9-layer 3D CNN for violence detection, obtaining a 91% accuracy on the Hockey Fight dataset [52]. Similarly, Li et al. [53] with a 10-layer 3D CNN alternating dense and transitional layers after a convolutional layer, achieved 98.3% accuracy on the Hockey Fight dataset, and 97.2% on the Crowd Violence dataset [49]. Transfer learning approaches based on 3D CNN also demonstrated good performances. For example, in our previous work [44], we used C3D [54], a 3D CNN pre-trained to classify sport categories, as a feature extractor, and a Support Vector Machine (SVM) classifier, with a 98.5% and a 99.2% accuracy on the Hockey Fight and the Crowd Violence respectively. Similary, Ullah et al. [55] used C3D as a feature extractor, but followed by fully connected layers for classification, with a good performance in both the Hockey Fight (96% accuracy) and Crowd Violence (98%) datasets. In addition to 3D CNNs, also the ConvLSTM architecture [56] has been proven effective in violence detection. To this end, Sudhakaran and Lanz [57] proposed to aggregate the spatial information extracted from the frames by 2D CNNs with a ConvLSTM, achieving a 97.1% accuracy on the Hockey Fight dataset, and 94.5% on the Crowd Violence dataset.

Therefore, deep learning-based techniques demonstrated their accuracy on datasets which are traditional in literature such as the Hockey Fight and Crowd Violence. However, there is still ongoing research to validate their robustness against false positives [58], and with real surveillance camera footages [59].

5. Conclusions

We presented a short survey about deep learning applications for three application domains connected to law enforcement: Face Recognition, Fingerprint Recognition, and Violence Detection. These three domains have some common characteristics. In fact, early methods to the computerization of related tasks are all rooted in Computer Visions, using techniques such as Principal Component Analysis, Image Binarization and Thinning, Optical Flow, etc. However, the use of deep learning techniques, such as Convolutional Neural Networks (2D and 3D) and ConvLSTMs, significantly improved the accuracy of automatic applications dealing with Face Recognition, Fingerprint Recognition, and Violence Detection.

While some of these deep learning techniques are being integrated in production systems, at least for Face and Fingerprint Recognition[1], there is still the need to investigate

[1] See, for example, the Italian system SARI, an extension of an Automated Fingerprint Identification Systems (AFIS) which supports Face Recognition [60].

their impact in real world applications. For example, concerning Face Recognition, there is a lack of research in understanding the effectiveness of face identification when only the two mugshots per subject commonly stored in law enforcement databases are available for training. Concerning Fingerprint Recognition, research is ongoing to get an effective extraction of minutiae from latent fingerprint images, which are available in crime scenes. Concerning Violence Detection, the accuracy of deep learning techniques with real surveillance cameras and their robustness to false positives are among the objectives of current research.

Moreover, to be effective in real applications, deep learning based techniques, as Artificial Intelligence in general, need to take into account concrete real time performances. In fact, as pointed out in [61], an intelligent answer preserves its importance only if given in time. Finally, as the evidence collected using AI should be explainable to a judge in a court [13], also Explainable AI (XAI) methods, capable to provide human understandable explanations of their results [62], should be investigated in the presented application domains, to avoid the use of deep learning techniques as mere “black boxes”.

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