A SYSTEM, METHOD AND COMPUTER READABLE MEDIUM FOR TRAINING A CONVOLUTIONAL NEURAL NETWORK MODEL AND A RECURRENT NEURAL NETWORK MODEL TO AUTOMATICALLY VERIFY OFFLINE SIGNATURES BASED ON IMAGE SEQUENCE

TECHNICAL FIELD

[0001] The present disclosure relates generally to a system, method and computer readable medium for training a Convolutional Neural Network (CNN) model and a Recurrent Neural Network (RNN) model to automatically verify offline signatures based on image sequence. Embodiments of the disclosure are related to a system, method and computer readable medium for verifying offline signatures by inputting the image sequence into the RNN model to learn the dependencies in the image sequence and output a confidence score.

BACKGROUND

[0002] Each person has their own unique signature that is generally used for purposes such as personal identification and verification of certain documents or legal transactions. The handwritten signatures are the results of such complex systems and coordinations within a human body and are reflective of certain personal traits and thus are unique among individuals. The handwritten signatures are hard to imitate or copy. Hence, these features led to the use of signature as a means of biometric identification. A handwritten signature is an important identifiable characteristic of an individual. They are non-contact, easy to obtain, and easy to accept. Additionally, signatures ensure protection and safety by enabling identification of original documents and ensuring that forged documents with false signatures are not authenticated.

[0003] The need of signature verification is no less important than the signature itself. As mentioned above, signature verification has various advantages such as acceptability of checkups and credit cards by financial institutions and e-commerce, computer user authentication, passports, getting access to certain security zones, to verify and approve certificates and contracts, and the ability to circumvent.

Handwritten signature verification belongs to the technical field of handwriting identification. Traditionally, signature verification was carried out manually with the help of an individual’s intellect and personal understanding which does not require any specialized hardware. However, the conventional techniques of manual based handwriting identification has revealed various shortcomings and defects in actual operation. One of the disadvantages of manually conducting signature verification is the lack of mutual cooperation mechanism of the appraisal agency, the non-standard appraisal standards for appraisal personnel, the uneven level of appraisal and difficulty in ensuring the accuracy of appraisal, and so on, which inevitably has a negative impact on the appraisal results.

[0004] The above disadvantage of manually conducting signature verification inevitably resulted in a need for using automation, normalization and other methods to deal with signature identification, which was originally a non-engineering field.

[0005] With the advent of time and developments in the field of deep learning, conventional signature recognition techniques employ manual design feature extraction, based on pictures or time series. However, an advantage of this conventional technique is that the manual design feature extraction takes a lot of time and effort. Another disadvantage of the above-mentioned conventional technique is that even slight changes in the external environment results in a need for the feature extraction process to be changed in order to adapt again. Moreover, as the number of manually designed features increase, maintenance work in this conventional technique becomes increasingly difficult. Additionally, each newly added feature may overlap or conflict with the existing feature, which requires a lot of time and manpower to resolve. Furthermore, in a real-world application, there are numerous handwritten signatures to acknowledge and verify in actual which further adds immense time and efforts to the existing drawbacks of this conventional technique.

[0006] Signature may be divided into online and offline (handwritten) signatures. Signature verification of online signatures use certain unique dynamic information as the input set points for signature verification, such as the online acquisition of the signer's stroke order, writing speed, pen pressure and other dynamic information and then use these dynamic information as signals. In the present times, verification of

online signatures entails comparing a forged signature with several examples of known valid signatures by examining the signs of forgery which includes the signatures written at a speed which is significantly slower than the genuine signatures, frequent change of the grasp of the writing implement, rounded line endings and beginnings, poor line quality with hesitant and shake of the line, retracing and patching and stops in places where the writing should be free. Additionally, multiple signal processing models such as hidden Markov chains, matrix analysis, Fourier change and other methods may also be employed.

[0007] Conventional techniques for recognition of offline signatures usually employ Convolutional Neural Networks (CNN). However, a disadvantage of such conventional techniques is that the location information of the features extracted using CNN is overlooked and ignored. Thus, for example, in such techniques, if a face is being recognized and if the mouth and eyes are swapped in an image, the face recognition model will verify the image and consider it as the same person.

[0008] Further, offline signatures only have picture data, and there is no dynamic information which makes it more difficult to verify. Existing technologies use artificial design feature extraction to convert picture information into feature information for comparison.

[0009] Owing to the fact that a plethora of tasks are performed virtually in the present day and age, there is a need for a solution that is capable of overcoming the drawbacks of the conventional techniques and enables automatic and accurate verification of offline signatures.

SUMMARY

[0010] The present disclosure relates generally to a system, method and computer readable medium for training a Convolutional Neural Network (CNN) model and a Recurrent Neural Network (RNN) model to automatically verify offline signatures based on image sequence. Embodiments of the disclosure are related to a system, method and computer readable medium for verifying offline signatures by inputting the image sequence into the RNN model to learn the dependencies in the image sequence

and output a confidence score.

[0011] The present invention is a new neural network architecture to deal with a new kind of network, which will translate a signature picture from left to right into a sequence, and then input this sequence to a recurrent network to learn the dependencies in the sequence. Embodiments of the present invention are more sensitive to forged signatures and are capable of an improved accuracy rate. Further, the verification method of the present invention is capable of verifying offline signatures, and it is more efficient than the conventional techniques in training, more sensitive to forged signatures that look real, and has higher authentication accuracy.

[0012] The system, method and computer readable medium disclosed in the present application are advantageous in several ways, including but not limited to, automatically verifying offline signatures based on image sequence, being capable of being implemented on a device having an imaging unit including but without limitation, a mobile device, a webcam, a surveillance camera, Single Lens Reflex (SLR) camera and/ or the like, processing images of the signatures captured without a restriction of any specific angle of view, increasing the efficiency in terms of speed and accuracy of the verification of signature(s) and the determination of authenticity, optimizing the accuracy of verification of signature(s) having similar handwriting, data sequence, flow, patterns and/ or the like, overcoming the requirement of human intervention, saving costs, time, manual effort due to increased efficiency and higher accuracy rate, resulting in higher sensitivity to forged signatures in comparison with the deep learning models used in conventional techniques

[0013] In a first aspect of the present disclosure, a system for training a Convolutional Neural Network (CNN) model and a Recurrent neural network (RNN) model to automatically verify offline signatures based on an image sequence is disclosed. The system may comprise a data collection unit for collecting at least one true signature and at least one false signature; a pre-processing unit for pre-processing a plurality of signature pairs and converting said plurality of signature pairs into a two-channel composite images; the Convolutional Neural Network (CNN) model for converting the two-channel composite image into the image sequence; and the Recurrent Neural

Network (RNN) model input with the image sequence to provide a confidence score, wherein the Recurrent Neural Network (RNN) model learns the dependency between a plurality of image blocks in the image sequence and outputs the confidence score based on at least one similarity in the image sequence.

[0014] According to an embodiment in conjunction to the first aspect of the present disclosure, the Convolutional Neural Network (CNN) model is a 6-layer Convolutional Neural Network (CNN), and the Recurrent Neural Network (RNN) model is a 2-layer Long Short Term Memory (LSTM).

[0015] According to an embodiment in conjunction to the first aspect of the present disclosure, the Convolutional Neural Network (CNN) model is trained using said plurality of signature pairs.

[0016] According to an embodiment in conjunction to the first aspect of the present disclosure, said plurality of signature pairs comprise said at least one true signature and said at least one true signature.

[0017] According to an embodiment in conjunction to the first aspect of the present disclosure, the plurality of signature pairs comprise said at least one true signature and said at least one false signature.

[0018] According to an embodiment in conjunction to the first aspect of the present disclosure, the two-channel composite image is of the size of 64 by 128 by 2 (64 * 128 * 2) pixels.

[0019] According to an embodiment in conjunction to the first aspect of the present disclosure, the Convolutional Neural Network (CNN) model comprises an input layer to receive the two-channel composite image.

[0020] According to an embodiment in conjunction to the first aspect of the present disclosure, the Convolutional Neural Network (CNN) model outputs the image

sequence with said plurality of image blocks, such that each image block has a height of one pixel.

[0021] According to an embodiment in conjunction to the first aspect of the present disclosure, the Convolutional Neural Network (CNN) model outputs the image sequence with said plurality of image blocks, such that each image block has a length of 31 pixel.

[0022] In a second aspect of the present disclosure, a method for training a Convolutional Neural Network (CNN) model and a Recurrent neural network (RNN) model to automatically verify offline signatures based on an image sequence is disclosed. The method may comprise collecting, by a data collection unit, at least one true signature and at least one false signature; pre-processing, by a pre-processing unit, said at least one true signature and at least one false signature to generate a two-channel composite image; converting, by the Convolutional Neural Network (CNN) model, the two-channel composite image into the image sequence; inputting the image sequence to the Recurrent Neural Network (RNN) model; learning, by the Recurrent Neural Network (RNN) model, the dependency between a plurality of image blocks in the image sequence; and outputting, by the Recurrent Neural Network (RNN) model, a confidence score based on at least one similarity in the image sequence

[0023] According to an embodiment in conjunction to the second aspect of the present disclosure, pre-processing, by the pre-processing unit, said at least one true signature and at least one false signature to generate a two-channel composite image comprises: pairing, by the pre-processing unit, said at least one true signature and said at least one false signature to form a plurality of signature pairs, converting, by the pre-processing unit, the plurality of signature pairs into single channel, adjusting, by the pre-processing unit, the size of the single channel images to a predetermined size, superimposing, by the pre-processing unit, the two images of the signature pair to generate the two-channel composite image.

[0024] According to an embodiment in conjunction to the second aspect of the present disclosure, said plurality of signature pairs is used for training the

Convolutional Neural Network (CNN) model.

[0025] According to an embodiment in conjunction to the second aspect of the present disclosure, said plurality of signature pairs comprise said at least one true signature and said at least one true signature.

[0026] According to an embodiment in conjunction to the second aspect of the present disclosure, said plurality of signature pairs comprise said at least one true signature and said at least one false signature.

[0027] According to an embodiment in conjunction to the second aspect of the present disclosure, the two-channel composite image is of the size of 64 by 128 by 2 (64 * 128 * 2) pixels.

[0028] According to an embodiment in conjunction to the second aspect of the present disclosure, the Convolutional Neural Network (CNN) model comprises an input layer to receive the two-channel composite image.

[0029] According to an embodiment in conjunction to the second aspect of the present disclosure, the Convolutional Neural Network (CNN) model outputs the image sequence with said plurality of image blocks, such that each image block has a height of one pixel.

[0030] According to an embodiment in conjunction to the second aspect of the present disclosure, the Convolutional Neural Network (CNN) model outputs the image sequence with said plurality of image blocks, such that each image block has a length of 31 pixel.

[0031] In a third aspect of the present disclosure, a computer readable medium storing a program comprising instructions that, when executed by a system, cause the system to train a Convolutional Neural Network (CNN) model and a Recurrent neural network (RNN) model to automatically verify offline signatures based on an image

sequence, is disclosed.

[0032] The following description is provided to facilitate an understanding of some of the innovative features unique to the disclosed embodiment and is not intended to be a full description. A full appreciation of the various aspects of the embodiments disclosed herein can be gained by taking into consideration the entire specification, claims, drawings, and abstract as a whole.

BRIEF DESCRIPTION OF THE DRAWINGS

[0033] **FIG. 1** is a block diagram depicting an example system **100** for training a Convolutional Neural Network (CNN) model and a Recurrent Neural Network (RNN) model to automatically verify offline signatures based on image sequence, in accordance with the disclosed embodiments.

[0034] **FIG. 2** is a block diagram depicting another example system **200** for training a Convolutional Neural Network (CNN) model and a Recurrent Neural Network (RNN) model to automatically verify offline signatures based on image sequence, in accordance with the disclosed embodiments.

[0035] **FIG. 3** is a flow diagram that illustrates an example method **300** training a Convolutional Neural Network (CNN) model and a Recurrent Neural Network (RNN) model to automatically verify offline signatures based on image sequence, in accordance with the disclosed embodiments.

[0036] **FIG. 4 i**s a flow diagram that illustrates an example method **400** for pre-processing signature data received from a data collection unit to train a Convolutional Neural Network (CNN) model, in accordance with the disclosed embodiments.

[0037] The summary above, as well as the following detailed description of illustrative embodiments, is better understood when read in conjunction with the appended drawings. For the purpose of illustrating the present disclosure, exemplary constructions of the disclosure are shown in the drawings. However, the disclosure is

not limited to specific methods and instrumentalities disclosed herein. Moreover, those in the art will understand that the drawings are not to scale. Wherever possible, like elements have been indicated by identical numbers.

DETAILED DESCRIPTION OF ILLUSTRATIVE EMBODIMENTS

[0038] The particular configurations discussed in the following description are non-limiting examples that can be varied and are cited merely to illustrate at least one embodiment and are not intended to limit the scope thereof.

[0039] A system, method and computer readable medium for training a Convolutional Neural Network (CNN) model and a Recurrent Neural Network (RNN) model to automatically verify offline signatures based on image sequence is disclosed. A data collection unit collects at least one true signature and at least one false signature. A signature pair is formed using said at least one true signature and said at least one false signature. A pre-processing unit is used for pre-processing a plurality of signature pairs and converting each signature pair into a two channel composite image. A CNN model is used for converting the two-channel composite image into an image sequence. A RNN model is inputted with the image sequence to provide a confidence score stating whether the signature is a true or false one. The RNN model learns the dependency between a plurality of image blocks of the image sequence and outputs the confidence score based on at least one similarity in the image sequence. The value of signature verification has been acknowledged in various fields and industries to enable effective authentication and verification, for example, banking and financial services, administrative services, Information Technology (IT), healthcare, government and non-profit organizations, insurance, judicial field and so on.

[0040] **FIG. 1** is a block diagram depicting an example system **100** for training a Convolutional Neural Network (CNN) model and a Recurrent Neural Network (RNN) model to automatically verify offline signatures based on image sequence, in accordance with the disclosed embodiments. The system **100** comprises a data collection unit **102**, a pre-processing unit **104**, the CNN model **106** and the RNN model

108.

[0041] The data collection unit **102** is used for collecting at least one true signature and at least one false signature of one or more persons. In an embodiment of the present invention, the false signature is a high imitation signature of a true signature. For example, the data collection unit **102** may collect electronic signatures of 1000 people and pick one person to forge several other signatures, keeping all the true signatures and false signatures image files to form a training set. In an embodiment of the present invention, the data collection unit **102** can have a signature collection means including, without limitation, a signature collection mobile app to collect true and false signatures of one or more persons using canvas. In an embodiment of the present invention, the data collection unit **102** may be an imaging unit of a mobile device or connected to the mobile device either locally or wirelessly.

[0042] The pre-processing unit **104** pre-processes the images by pairing at least one true signature with said at least one true signature and at least one true signature with said at least one false signature to form a plurality of signature pairs and generating one or more two-channel composite images by converting the plurality of signature pairs into one channel, adjusting the size of the one channel images to a predetermined size and superimposing the two images of the respective signature pair. In an embodiment of the present invention, the one channel images of a signature pair are greyscale images. In an example, if 10 true signatures and 10 false signatures are collected from one person, a total of 45 true and true signature pairs may be formed using the formula (n*(n-1))/2, wherein since the number of signatures is 10, that is n=10, then the total true and true signature pairs (10* 9)/2 = 45. In the above example, a total of 100 true and false signature pairs may be formed and accordingly, the total signature pairs in the training set attained by the 10 signatures would be 145. In an embodiment of the present invention, the one channel image is adjusted to the size 64 * 128 and the generated two-channel composite image is 64 * 128 * 2. In an embodiment of the present invention, the pre-processed signature data (two-channel composite image) generated by the pre-processing unit **104** is sent to train the CNN model **106**.

[0043] The CNN model **106** is used for converting the two-channel composite image into an image sequence. In an embodiment of the present invention, the image sequence is a feature sequence which refers to an image sequence having certain defined variables or attributes that denotes a particular feature shown in the respective image. In an embodiment of the present invention, the CNN model **106** is a six (6) layer CNN. In an embodiment of the present invention, in a 6-layer CNN model **106**, the input layer is changed to accept dual channels. In an example, the CNN model **106** may be inputted with an image of size 64 * 128 and a feature sequence of 31 * 512 may be generated by the CNN model **212**, which represents that the picture is divided into 31 equal blocks from left to the right, each block containing 512 features. For example, the two-channel composite image with the size of 64 * 128 * 2 in the above example is considered as an input to CNN model **106**. In an embodiment of the present invention, two pooling layers are put separately after the first layer and the second layer of the CNN model **106**. The third, fourth, fifth and sixth layers of the CNN model **106** have a convolution kernel with two step on image height and one step on image width. In an embodiment of the present invention, the CNN model **106** will change the height from 64 to 1 and the length to 31. In the above example, a 31 * 512 image sequence will be obtained. An example 6-layer CNN model **106** showing all layers and its corresponding output is shown in **Table 1**. Each layer will learn the feature from low level to high level.

Table 1

Convolutional Layers	Explanation	Output size
1	Conv 3*3, 32 filters and maxpooling 2*2, stride=2	32*64*32
2	Conv 3*3, 64 filters and maxpooling 2*2, stride=2	16*32*64
3	Conv 3*3, 128 filters and maxpooling 2*1, stride=(2, 1)	8*32*128

4	Conv 3*3, 256 filters and maxpooling 2*1, stride=(2, 1)	4*32*256
5	Conv 3*3, 512 filters and maxpooling 2*1, stride=(2, 1)	2*32*512
6	Conv 2*2, 512 filters, padding=valid	1*31*512

[0044] The image sequence obtained from the CNN model **106** is input into the RNN model **108.** In an embodiment of the present invention, the RNN model **108** is a Long Short Term Memory (LSTM) which is a kind of recurrent neural network that is used to store long sequence information In an embodiment of the present invention, the RNN model **108** is a two-layer bidirectional LSTM.

[0045] The RNN model **108** is inputted with the image sequence to provide a confidence score. The RNN model **108** learns the dependency between a plurality of blocks in the image sequence and outputs the confidence score based on at least one similarity in the image sequence. In an embodiment of the present invention, the RNN model **108** is connected to a new output layer with only one neuron, and the output result will be either 0 or 1. When the input is a true and true signature pair, the output is 1, and when the input is a true and false signature pair, the output is 0. In some embodiments of the present invention, the two-channel composite images input to train the convolutional neural network may be automatically labelled in a binary allocation, for example ‘0’ for an image representing a signature pair of a true signature and a false signature, ‘1’ for an image representing a signature pair of a true signature and a true signature. The output of the recurrent neural network may be a confidence score between the values 0 and 1 (floating point number). In some embodiments of the present invention, a threshold may be predefined, such as a median value, (for example 0.5) to the output of the recurrent neural network, and the output may be deemed as a “positive sample” if the confidence score is greater than the threshold value (for example more than 0.5), and a “negative sample” if the confidence score is below the threshold value (for example less than 0.5). In some embodiments of the present invention, the confidence score may be generated as a percentage of confidence, fractions, true/false score and/ or the like.

[0046] **FIG. 2** is a block diagram depicting another example system **200** for training a Convolutional Neural Network (CNN) model and a Recurrent Neural Network (RNN) model to automatically verify offline signatures based on image sequence, in accordance with the disclosed embodiments. The system **200** comprises a client side **202** for collecting the true and false signatures of various persons and a server side **204** for verifying offline signatures based on image sequence. The client side **202** comprises a data collection unit **201** for collecting at least one true signature and at least one false signature of one or more persons. In an embodiment of the present invention, the false signature is a high imitation signature of a true signature. The data collection unit **201** on the client side **202** can have a signature collection means including, without limitation, a signature collection mobile app to collect true and false signatures of one or more persons using canvas. In an embodiment of the present invention, the system may be implemented on the client side, for example being a mobile device, where images of offline signatures are captured using the imaging unit of the mobile device or an external imaging unit such as a webcam, a surveillance camera, Single Lens Reflex (SLR) camera and/ or the like that is either connected locally to the mobile device or wirelessly such as via the internet, Bluetooth, Near-Field-Communication and/ or the like. In an embodiment of the present invention, the data collection unit **201** may be an imaging unit of the mobile device or connected to the mobile device either locally or wirelessly. The server side **204** comprises a collection module **206** and a training module **208**. The collection module **206** comprises a pre-processing unit **210.** The collection module **206** receives the images collected by the data collection unit **201** and the pre-processing unit **210** of the collection module **206** pre-processes the images by pairing at least one true signature with said at least one true signature and at least one true signature with said at least one false signature to form a plurality of signature pairs and generating one or more two-channel composite images by converting the plurality of signature pairs into one channel, adjusting the size of the one channel images to a predetermined size and superimposing the two images of the respective signature pair. In an embodiment of the present invention, the one channel images of a signature pair are greyscale images. In an embodiment of the present invention, the pre-processing unit **210** pre-processes the collected signature data received from the client side **202** and converts it to the two-channel composite images that are used to train the training module **208.**

In an embodiment of the present invention, the one channel image is adjusted to the size 64 * 128 and the generated two-channel composite image is 64 * 128 * 2.

[0047] The training module **208** comprises a Convolutional Neural Network (CNN) model **212** and a Recurrent Neural Network (RNN) model **214**. In an embodiment of the present invention, the CNN model **212** is a six (6) layer CNN. In an embodiment of the present invention, the RNN model **214** is a Long Short Term Memory (LSTM). The training module **208** receives said one or more two-channel composite images generated by the pre-processing unit **210** and the CNN model **212** of the training module **208** converts said one or more two channel images to an image sequence. In an embodiment of the present invention, a first layer of the CNN is adapted to accept dual channel images. The RNN model **214** receives the image sequence generated by the CNN model **212** and produces a confidence score. In an embodiment of the present invention, the RNN model **214** is a two-layer bidirectional LSTM. The RNN model **214** learns the dependency between plurality of image blocks in the image sequence and outputs the confidence score based on at least one similarity in the image sequence. In the above example, the generated feature sequence is fed into the RNN model **214**, being for example a LSTM model, to learn the dependency between the 31 blocks, and then output the similarity. After training, the training module **208** is capable of being used in real time applications for inference and verification of offline signatures.

[0048] **FIG. 3** is a flow diagram that illustrates an example method **300** training a Convolutional Neural Network (CNN) model and a Recurrent Neural Network (RNN) model to automatically verify offline signatures based on image sequence, in accordance with the disclosed embodiments. The method **300** can be implemented, for example, at block **302,** by collecting at least one true signature and at least one false signature of one or more persons using a data collection unit. In an embodiment of the present invention, the false signature is a high imitation signature of a true signature. As at block **304**, the signature data collected by the data collection unit is sent to a pre-processing unit. As at block **306**, the pre-processing unit pre-processes said at least one true signature and at least one false signature to generate a two-channel composite image. As at block **308**, the pre-processed signature data (the two-

channel composite image) generated by the pre-processing unit is sent to a Convolutional Neural Network (CNN) model. In an embodiment of the present invention, the pre-processing unit pre-processes the collected signature data and converts it to the two-channel composite images that are used to train the Convolutional Neural Network (CNN) model. As at block **310**, the method **300** can be implemented by converting, by the CNN model, said two channel image to an image sequence. In an embodiment of the present invention, the image sequence is a feature sequence which refers to an image sequence having certain defined variables or attributes that denotes a particular feature shown in the respective image. In an embodiment of the present invention, a first layer of the CNN is adapted to accept dual channel images. In an embodiment of the present invention, the image sequence is a feature sequence which refers to an image sequence having certain defined variables or attributes that denotes a particular feature shown in the respective image. In an example, the CNN model may be inputted with an image of size 64 * 128 and a feature sequence of 31 * 512 may be generated by the CNN model, which represents that the picture is divided into 31 equal blocks from left to the right, each block containing 512 features. Thereafter, as at block **312**, the image sequence is inputted to a Recurrent Neural Network (RNN) model. In an embodiment of the present invention, the RNN model is a Long Short Term Memory (LSTM). As at block **314**, the method **300** can be implemented by, learning, by the RNN model, the dependency between a plurality of image blocks in the image sequence and outputting, by the RNN model, a confidence score based on at least one similarity in the image sequence as at block **316**. In an embodiment of the present invention, the RNN model is a two-layer bidirectional LSTM. In the above example, the generated feature sequence is sent to the RNN model, being for example a LSTM model, to learn the dependency between the 31 blocks, and then output a confidence score based on the similarity.

[0049] In some embodiments of the present invention, the two-channel composite images input to train the convolutional neural network may be automatically labelled in a binary allocation, for example ‘0’ for an image representing a signature pair of a true signature and a false signature, ‘1’ for an image representing a signature pair of a true signature and a true signature. The output of the recurrent neural network may be a confidence score between the values 0 and 1 (floating point number). In some embodiments of the present invention, a threshold may be predefined, such as a

median value, (for example 0.5) to the output of the recurrent neural network, and the output may be deemed as a “positive sample” if the confidence score is greater than the threshold value (for example more than 0.5), and a “negative sample” if the confidence score is below the threshold value (for example less than 0.5). In some embodiments of the present invention, the confidence score may be generated as a percentage of confidence, fractions, true/false score and/ or the like.

[0050] **FIG. 4 i**s a flow diagram that illustrates an example method **400** for pre-processing signature data received from a data collection unit to train a Convolutional Neural Network (CNN) model, in accordance with the disclosed embodiments. In an embodiment of the present invention, the signature data may be collected by the data collection unit using the example method **300** as described in **FIG. 3** of the present disclosure. As at block **402,** the method **400** can be implemented by, for example, pairing, by a pre-processing unit, at least one true signature and at least one false signature to form a plurality of signature pairs. In an embodiment of the present invention, said at least one true signature is paired with said at least one true signature and said at least one true signature is paired with said at least one false signature to form a plurality of signature pairs. In an embodiment of the present invention, the false signatures are high imitation signatures of a true signature. As at block **404**, converting, by the pre-processing unit, the plurality of signature pairs into a single channel. In an embodiment of the present invention, the single channel images of a signature pair are greyscale images. As at block **406**, adjusting, by the pre-processing unit, the size of the single channel images to a predetermined size. As at block **408**, superimposing, by the pre-processing unit, the two images of the signature pair to generate the two-channel composite image. In an embodiment of the present invention, the one channel image is adjusted to the size 64 * 128 and the generated two-channel composite image is 64 * 128 * 2.

[0051] Persons skilled in the art will understand that aligned human faces have positional commonality, so positional information is not important in facial recognition, but signatures have greater freedom, and stroke positional information is particularly important. The present invention is a new neural network architecture to deal with this kind of network, which will translate a signature picture from left to right into a sequence, and then input this sequence to a recurrent network to learn the

dependencies in the plurality of image blocks in an image sequence. Embodiments of the present invention are more sensitive to forged signatures and are capable of an improved accuracy rate. Further, the verification method of the present invention is capable of verifying offline signatures, and it is more efficient than the conventional techniques in training, more sensitive to forged signatures that look real, and has higher authentication accuracy. It should be noted that the present invention uses the signature pair as images, processes and converts the images into one or more two-channel composite images.

[0052] The present invention also discloses a computer readable medium storing a program comprising instructions that, when executed by a system, cause the system to train a Convolutional Neural Network (CNN) model and a Recurrent neural network (RNN) model to automatically verify offline signatures based on an image sequence.

[0053] It will be appreciated that variations of the above disclosed and other features and functions, or alternatives thereof, may be desirably combined into many other different systems or applications. Also, various presently unforeseen or unanticipated alternatives, modifications, variations or improvements therein may be subsequently made by those skilled in the art which are also intended to be encompassed by the following claims.

[0054] Although embodiments of the current disclosure have been described comprehensively in considerable detail to cover the possible aspects, those skilled in the art would recognize that other versions of the disclosure are also possible.

CLAIMS

What is claimed is:

1. A system for training a Convolutional Neural Network (CNN) model and a Recurrent neural network (RNN) model to automatically verify offline signatures based on an image sequence, comprising:

a data collection unit for collecting at least one true signature and at least one false signature;

a pre-processing unit for pre-processing a plurality of signature pairs and converting said plurality of signature pairs into a two-channel composite images;

the Convolutional Neural Network (CNN) model for converting the two-channel composite image into the image sequence; and

the Recurrent Neural Network (RNN) model input with the image sequence to provide a confidence score,

wherein the Recurrent Neural Network (RNN) model learns the dependency between a plurality of image blocks in the image sequence and outputs the confidence score based on at least one similarity in the image sequence.

2. The system of claim **1**, wherein the Convolutional Neural Network (CNN) model is a 6-layer Convolutional Neural Network (CNN), and the Recurrent Neural Network (RNN) model is a 2-layer Long Short Term Memory (LSTM).

3. The system of claim **1**, wherein the Convolutional Neural Network (CNN) model is trained using said plurality of signature pairs.

4. The system of claim **1**, wherein said plurality of signature pairs comprise said at least one true signature and said at least one true signature.

5. The system of claim **1**, wherein the plurality of signature pairs comprise said at least one true signature and said at least one false signature.

6. The system of claim **1**, wherein the two-channel composite image is of the size of 64 by 128 by 2 (64 * 128 * 2) pixels.

7. The system of claim **1**, wherein the Convolutional Neural Network (CNN) model comprises an input layer to receive the two-channel composite image.

8. The system of claim **1**, wherein the Convolutional Neural Network (CNN) model outputs the image sequence with said plurality of image blocks, such that each image block has a height of one pixel.

9. The system of claim **1**, wherein the Convolutional Neural Network (CNN) model outputs the image sequence with said plurality of image blocks, such that each image block has a length of 31 pixel.

10. A method for training a Convolutional Neural Network (CNN) model and a Recurrent neural network (RNN) model to automatically verify offline signatures based on an image sequence, comprising:

collecting, by a data collection unit, at least one true signature and at least one false signature;

pre-processing, by a pre-processing unit, said at least one true signature and at least one false signature to generate a two-channel composite image;

converting, by the Convolutional Neural Network (CNN) model, the two-channel composite image into the image sequence;

inputting the image sequence to the Recurrent Neural Network (RNN) model;

learning, by the Recurrent Neural Network (RNN) model, the dependency between a plurality of image blocks in the image sequence; and

outputting, by the Recurrent Neural Network (RNN) model, a confidence score based on at least one similarity in the image sequence.

11. The method of claim **10** wherein pre-processing, by the pre-processing unit, said at least one true signature and at least one false signature to generate a two-channel composite image comprises:

pairing, by the pre-processing unit, said at least one true signature and said at least one false signature to form a plurality of signature pairs;

converting, by the pre-processing unit, the plurality of signature pairs into single channel;

adjusting, by the pre-processing unit, the size of the single channel images to a predetermined size; and

superimposing, by the pre-processing unit, the two images of the signature pair to generate the two-channel composite image.

12. The method of claim **11**, wherein said plurality of signature pairs is used for training the Convolutional Neural Network (CNN) model.

13. The method of claim **11**, wherein said plurality of signature pairs comprise said at least one true signature and said at least one true signature.

14. The method of claim **11**, wherein said plurality of signature pairs comprise said at least one true signature and said at least one false signature.

15. The method of claim **10**, wherein the two-channel composite image is of the size of 64 by 128 by 2 (64 * 128 * 2) pixels.

16. The method of claim **10**, wherein the Convolutional Neural Network (CNN) model comprises an input layer to receive the two-channel composite image.

17. The method of claim **10**, wherein the Convolutional Neural Network (CNN) model outputs the image sequence with said plurality of image blocks, such that each image block has a height of one pixel.

18. The method of claim **10**, wherein the Convolutional Neural Network (CNN) model outputs the image sequence with said plurality of image blocks, such that each image block has a length of 31 pixel.

19. A computer readable medium storing a program comprising instructions that, when executed by a system, cause the system to train a Convolutional Neural Network (CNN) model and a Recurrent neural network (RNN) model to automatically verify offline signatures based on an image sequence, of any of claims **10**-**18**.