Signature Feature Extraction and Classification

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Introduction

In today's world where the advancement in computer science has made the accuracy of machine in many task close to human level be it object recognition, face recognition or any such related field. But the area of signature recognition or classification still is pretty far from being close to human level accuracy. Signature is a person's identity that uniquely identifies it in legal works and as we can expect there are greater risks involved. So even today almost all of the places where signature verification is required we need a human for that purpose since there almost no margin for error due to the high stakes of someone involved.

Since the signature recognition has nothing to do with the color used and the other typical properties of an image then the use of CNN becomes effective less and much more time consuming since in CNN we extract many properties which are in this case prove to be redundant.

In this report we present a new model for signature classification which uses some basic and advanced image processing techniques to extract certain features that are used to uniquely identify someone's signature.

The extracted features are then input into some classification models to testify the accuracy and some conclusions based on which is made.

Dataset Description

The dataset we used here is GPDS, which provides us with 300 users' data with each user's data contains 54 images of signature in which 24 are original images and 30 are forged images by some skilled person.

Fig 1. Original signature of some user.

Fig 2. Signature forged by skilled personal.

Preprocessing

Before we could extract the features we need to preprocess the image. As shown in Fig 1 and Fig 2 the width and stroke can vary a great deal and also the means used for signature can also vary. So, we cannot directly extract the features as the feature could vary a lot for a single person. So, we used some techniques such that the effects of all render ineffective.

So, we used the following procedure before extracting features:

- First read the image.
- Convert the image into binary image.
- Then skeletonize the image to form single line image.
- After this we need to invert the image and we get image as shown in Fig 3.

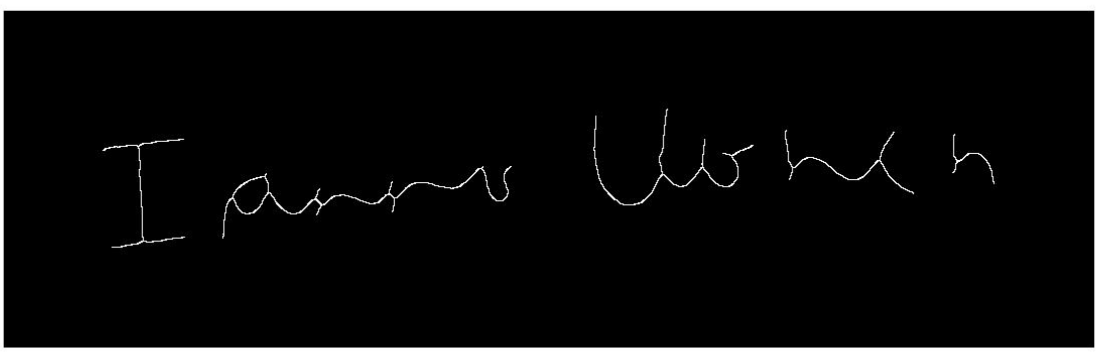

Fig 3. Image in fig 1 after preprocessing.

The Feature Set

Since we need to make a classifier we needed set of features that can be used to identify each person's signature as uniquely as possible, so after some research over the internet we used the following features for our purpose:

- Center of Pixels (In both the directions).
- Total Number of Parts.
- Number of Isolated Points.
- Distance between Centers and Center of Masses.
- Average Height of the Signature.
- Count of the Pixels.
- Count of Harris Points.
- Degree of Skewness of image.
- Degree of kurtosis in image.

Center of Pixels (In both the directions): Just like in physics where the Center of mass is the measure of the group of objects (masses). Here we used the center of pixels instead with same ideology to map the collective pixels onto one single point.

Total Number of Parts: Different person's signatures are made of several number of disjoint parts due to one's habit of lifting the pen. This property can be crucial while classifying the signature.
For example: - The image used in this report fig 1,2,3 have total number of parts = 5.

Number of Isolated Points: This feature as the name suggests counts the points that are not connected to any other pixels (in fig 3). This feature is selected due to the fact that despite the name of many person, they draw some random dots (due to the flow) and this can be a prominent feature to find the distinction between two persons with same name as well as different names.

Distance between Effective Centers and Center of Masses:
Here effective centers are used which means the centers of the image obtained after drawing a tight rectangle across the signature. The center of masses is same as explained in the first feature.
We calculated the distance between both type of centers.

Average Height of the Signature: This feature was required to estimate the sleekness of the signature. Many people make the first letter of the signature huge then the rest follows a constant height. So, the centers can vary within one person's data a bit, so, to cope up this feature neutralizes this effect.

Count of the Pixels: All the features listed till now are all somehow related to the collective proper of distribution of pixels and only gets affected by the distribution of the pixels regardless of anything, this can be monotonous for similarly distributed signatures and will affect the model. So, to normalize this effect we also included the count of pixels set in the skeleton of the image. Since the skeleton of a particular person's signature cannot vary much and only single pixel lines are used to trace the original image. So this count cannot vary much and hence is unique for a particular person.

Count of Harris Points: Till now there is no feature for the curves and corners of the image that needless to say is a must be looked at aspect for any signature. Harris Corner Detector is a corner detection operator that is commonly used in computer vision algorithms to extract corners and infer features of an image. This feature is a count that maps the curves and corners into an integer.

General Algorithm for Harris Point Counts:

1. Consider taking an image patch over the (x, y) and shifting it by (Δx, Δy).
2. The sum of squared differences (SSD) between these two patches, denoted f(x,y) , is given by:

$$f(x, y) = \sum_{(xk,\, yk) \in W} ((I(x_k,y_k)-I(x_k+\Delta x,y_k+\Delta y))^2$$

3. I(x+Δx, y+Δy) can be estimated using Taylor's Expansion as $I(x+\Delta x, y+\Delta y) = I(x,y) + I_x(x,y)\Delta x + I_y(x,y)\Delta y$.
   Where I_x and I_y are partial derivatives.

4. So we can say

$$f(x, y) = \sum_{(xk,\, yk) \in W} (I_x(x,y)\Delta x + I_y(x,y)\Delta y)^2$$

Thus we calculate f(x, y) for each location and add them for the image.

Degree of Skewness of image: In probability theory and statistics, **skewness** is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean. The **skewness** value can be positive or negative, or undefined. This property can be used to find the skewness of the image. Since image is also a vector of vectors. We first found out the skewness value of a single row and then the skewness value of those values.

Degree of Kurtosis of image: Just Like Skewness, kurtosis is also a property of statistics where we compare the distribution with normal distribution and try to find out the tail. Low kurtosis means high tail.

The Model

We implemented two types of models:

➢ User Recognition

After we find out the feature set of all images, we need a classification algorithm to complete the prediction model. Though there are many classification algorithms available, we tried the following algorithms after looking at the properties of the dataset (i.e. smaller number of data per class and higher number of classes):

- KNN
- SVM
- ANN

The table below contains summary of the model:

No of Users / Model Name	30	100
KNN	62%	40%
SVM	87%	72%
ANN	24%	17%