

# Off-line Human Signature Recognition System Based on Histogram Analysis using MATLAB

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## ABSTRACT

Handwritten signatures are considered as the most natural method of authenticating a person's identity. Human signatures can be handled as an image and used in a scanned document is a promising facility for many banking and insurance related business activities. The signatures of the same person vary with time, age of the person and also because of the emotional state of a person. This paper present an off-line human signature recognition system based on histogram analysis. The main steps of constructing a signature recognition system are discussed and experiments on the values of cumulative distribution function (CDF).The off-line signature recognition and verification is implemented using MATLAB.

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## 1. Introduction

In the past years, biometrics research has always been the focus of interests for scientists and engineers. In the present year some industries, these systems are being replaced by much more advanced techniques to identify a person. These techniques are called biometrics, which involve checking a person's biological traits such as face, fingerprint, iris, retina, voice, signature etc. Hand written signatures are accepted means of a person's identification in almost all government, legal and commercial transactions. Particularly, handwriting is believed to be singular, exclusive and personal for individuals. Handwriting signature is the most popular identification method socially and legally which has been used widely in the bank check and credit card transactions, document certification, etc. There are two types of signature recognition systems namely, An Offline Signature or static recognition system and An Online Signature or dynamic recognition system.

An Offline Signature or static recognition system deals with signatures that have been written on paper and digitized by scanning. Off- line handwriting recognition systems are more difficult than online systems as dynamic information like duration, time ordering, number of strokes, and direction of writing are lost. An Online Signature or dynamic recognition system depends on a digitizing surface to capture dynamic features like pressure, speed, direction etc. In this paper deals with an off-line signature recognition and verification system.

## 2. Related work

In the last few decades, many approaches have been developed in the recognition and verification system, which approached the offline signature verification problem. An offline signature verification system based on DWT and common features extraction has achieved good verification measure with low false acceptance rate of 1.56% and low

average rate of 6.23% and false rejection rate of 10.9% [1]. An offline signature recognition using modular neural network and fuzzy reference system uses separate modules with features from edge detection, curvelet transform, Hough transform and combines the outputs from all these modules has achieved an accuracy of 96.6%[2]. The method relies on global features that summarize different aspects of signature shape and dynamics of signature production. For designing the algorithm, they have tried to detect the signature without paying any attention to the thickness and size of it [3]. A DWT based Off-line Signature Verification system using Angular Features use four bands from the DWT. The approximation band is skeletonized. The angular features are obtained by dividing the signature image into number of blocks and are used for comparison. The values of FAR and FRR measured at optimal threshold are said to be better compared to that of existing methods[4]. A signature identification system uses the rotated complex wavelet filters and dual tree complex wavelet transform together to extract the features which represent the information in twelve different directions. The results of this method are superior to DWT[5].

An offline handwritten signature identification and verification uses a feature extraction method based on Gabor wavelet transform and Gabor wavelet coefficients pertaining to different frequencies and directions are fed to a shortest weighted distance based classifier. The CCR and EER of the system 100% and 15% respectively on a Persian signature database [6]. An introduction to the concept of multi-scale saliency features to define signature characteristics [7] and also used it for signature verification [8]. An intra-model score level fusion for offline signatures using the angular features verifies the signatures based on correlation and distance based metrics and has reported better FAR, FRR and EER compared to the existing algorithms[9]. Offline signature verification has

been done based on grey level information using text features [10].

**3. Image Histogram**

An image histogram is a type of histogram that acts as a graphical representation of the tonal distribution in a digital image. The histogram plots the number of pixels in the image (vertical axis) with a particular brightness value (horizontal axis). In the field of computer vision, image histograms can be useful tools for thresholding. Because the information contained in the graph is a representation of pixel distribution as a function of lightness or tonal variation, image histograms can be analyzed for peaks and/or valleys [11].

**3.1 Histogram processing**

The histogram of a digital image with L total possible intensity levels in the range [0, G] is defined as the discrete function:  $H(i_m) = n_m$  Where,

- $i_m$  is the  $m_{th}$  intensity level in the interval [0, G],
- $n_m$  is the number of pixels in the image whose intensity level is  $i_m$
- G is [255 for images of class uint8, 65535 for images class uint16 and 1.0 for images of class double]

**3.2 Normalized Histogram**

Normalized histograms can be obtained by dividing all elements of  $H(i_m)$  by the total number of pixels ( $n$ ) in the image:

$$N(i_m) = \frac{H(i_m)}{n} = \frac{n_m}{n}, \text{ for } m = 1, 2, \dots, L$$

**3.3 Histogram Equalization**

Probability distributions are such that the total sum of the set of outcomes must be equal to 1 and the probability corresponding to a single outcome of interval of outcomes must be between 0 and 1. Histogram Equalization is a method which increases the dynamic range of the gray-level in a low-contrast image to cover full range of gray-levels. Histogram equalization is achieved by having a transformation function  $T(i)$ , which can be defined to be the Cumulative Distribution Function (CDF) of a given Probability Density Function (PDF) of gray-levels in a given image (the histogram of an image can be considered as the approximation of the PDF of that image). This transformation is called intensity-levels equalization process and it's nothing more than the cumulative distribution function (CDF).

$$S_m = T(i_m) = \sum_j^m \frac{H(i_j)}{n} = \sum_j^m \frac{n_j}{n}$$

for  $m = 1, 2, \dots, L$  and  $S_m$  is Intensity value of the output image corresponding to value  $i_m$  in the input image.

**4. Proposed Methodology**

The Proposed method for an Offline Signature or static recognition system is shown figure-1

**4.1 Signature Image Acquisition & Preprocessing**

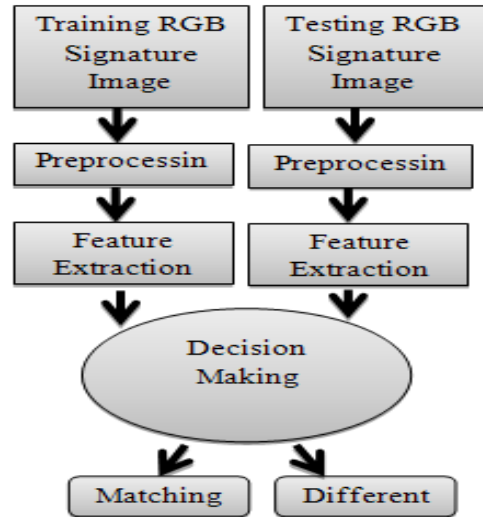
At first taking of my five similar signatures on a white paper by itself and another two similar signatures on a same white paper by another person. After scan this signature paper each image resized to 256x256 and save it in JPEG (Joint Photographic Experts Group) format.

**4.2 Feature Extraction**

After preprocessing the Signature undergo further processing are following:

- ✓ Convert Preprocessing RGB images into gray images by using `rgb2gray()` command and filtering these gray images by using `medfilt2([3 x 3])` filter command in MATLAB.
- ✓ Next apply Histogram processing, Normalized histogram and Histogram Equalization process for each signature `img1` to `img7`

- ✓ Taking signature `img1` as Training image
- ✓ Now Calculate the difference of cdf (Training image value<sub>i</sub>) –cdf (Testing image value<sub>j</sub>), where  $i, j = 1, 2, 3, \dots, 256$
- ✓ If the values of this difference is  $< 0.01$  then it counts as `matched_data` otherwise counts as `non_matched_data`
- ✓ Calculate `total_matched_percentage = (matched_data / total_data) * 100`
- If `total_matched_percentage`  $\geq 90$ , then Decision is “Matching” otherwise “Different” Signature by another person.



**Figure 1. Proposed Algorithm**

**4.3 Experimental Results**

This section reports some experimental results obtained using our recognition system. The experiment applied to 100 signature images of 20 persons. The experimental platform is the software is Matlab. The recognition performance is evaluated using different distance measure because the difference of cdf (Training image value<sub>i</sub>) –cdf (Testing image value<sub>j</sub>), where  $i, j = 1, 2, 3, \dots, 256$  are vary for different person. Experimental results are shown in Table 1. We have achieved 90-100% efficiency for various test data's.

**Table 1. Experimental results for image 1, 2 and 7**

Training image	Testing image	Matching percentage	Decision Making
Img1	Img2	100%	Matching
Img1	Img3	98.83%	Matching
Img1	Img4	98.44%	Matching
Img1	Img5	97.67%	Matching
Img1	Img6	62.5%	Different
Img1	Img7	65.62%	Different
Img1	Img1	100%	Matching

**5. Conclusions**

In this publication we devolve an off-line human signature recognition system based on histogram analysis. The main steps of constructing a signature recognition system are discussed and experiments on the values of cumulative distribution function. This paper helps in detecting the exact person and it provides more accuracy of verifying signatures. We have achieved 90-100% efficiency for various test data's.

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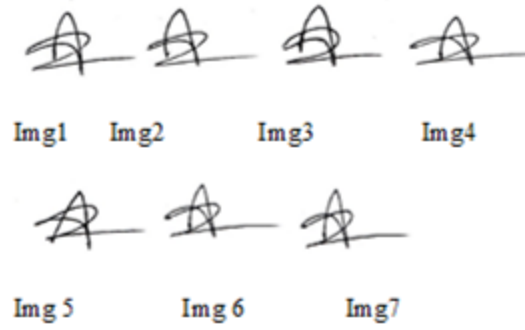


Figure 2. Scanned Signature Images

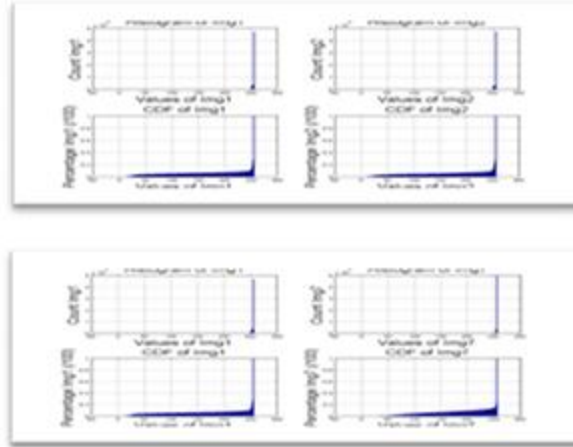


Figure 3. Histogram and CDF of Img1, Img2 & Img 7

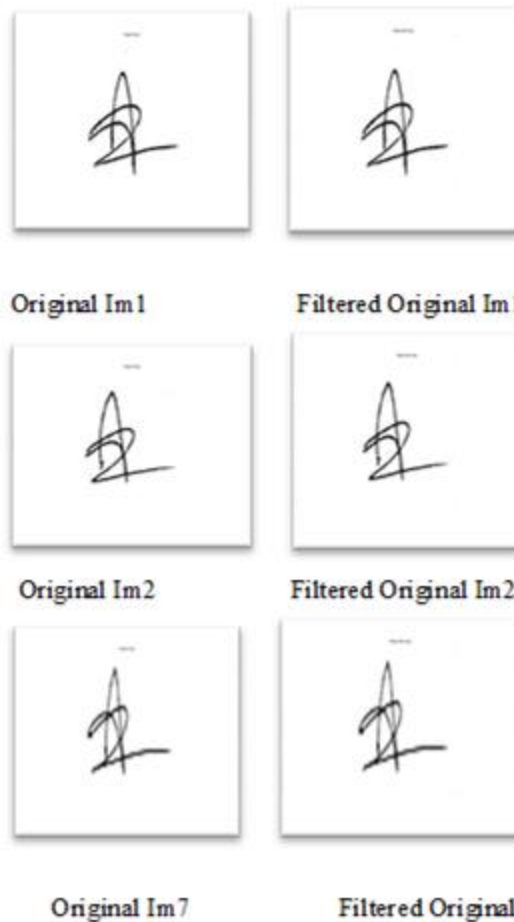


Figure 4. Original and Filtered of Img1, Img2 & Img 7

**Table 2. Intensity values of CDF for img 1**

0.0001, 0.0002, 0.0003, 0.0008, 0.0013, 0.0014, 0.0017, 0.0020, 0.0025, 0.0031, 0.0035, 0.0040, 0.0048, 0.0056, 0.0065, 0.0073,
0.0083, 0.0094, 0.0107, 0.0123, 0.0137, 0.0153, 0.0169, 0.0188, 0.0209, 0.0228, 0.0245, 0.0259, 0.0274, 0.0295, 0.0309, 0.0325,
0.0340, 0.0349, 0.0358, 0.0364, 0.0371, 0.0379, 0.0384, 0.0388, 0.0392, 0.0397, 0.0401, 0.0403, 0.0406, 0.0408, 0.0413, 0.0416,
0.0417, 0.0420, 0.0423, 0.0426, 0.0430, 0.0433, 0.0436, 0.0438, 0.0442, 0.0443, 0.0444, 0.0448, 0.0450, 0.0451, 0.0454, 0.0455,
0.0458, 0.0462, 0.0464, 0.0467, 0.0468, 0.0471, 0.0471, 0.0473, 0.0476, 0.0478, 0.0480, 0.0483, 0.0485, 0.0488, 0.0490, 0.0493,
0.0496, 0.0497, 0.0500, 0.0502, 0.0504, 0.0506, 0.0509, 0.0511, 0.0513, 0.0517, 0.0521, 0.0522, 0.0524, 0.0526, 0.0529, 0.0531,
0.0533, 0.0535, 0.0538, 0.0539, 0.0541, 0.0543, 0.0547, 0.0548, 0.0549, 0.0551, 0.0553, 0.0555, 0.0557, 0.0558, 0.0560, 0.0562,
0.0563, 0.0564, 0.0567, 0.0569, 0.0571, 0.0574, 0.0574, 0.0578, 0.0579, 0.0582, 0.0584, 0.0585, 0.0588, 0.0590, 0.0592, 0.0594,
0.0597, 0.0600, 0.0603, 0.0605, 0.0606, 0.0608, 0.0609, 0.0612, 0.0613, 0.0614, 0.0617, 0.0618, 0.0619, 0.0619, 0.0621, 0.0622,
0.0624, 0.0625, 0.0626, 0.0629, 0.0630, 0.0632, 0.0636, 0.0638, 0.0639, 0.0642, 0.0642, 0.0644, 0.0645, 0.0648, 0.0651, 0.0652,
0.0655, 0.0657, 0.0659, 0.0660, 0.0662, 0.0665, 0.0667, 0.0669, 0.0671, 0.0673, 0.0676, 0.0677, 0.0679, 0.0682, 0.0683, 0.0686,
0.0688, 0.0691, 0.0693, 0.0695, 0.0697, 0.0699, 0.0701, 0.0703, 0.0704, 0.0706, 0.0709, 0.0711, 0.0713, 0.0715, 0.0716, 0.0719,
0.0720, 0.0721, 0.0724, 0.0727, 0.0731, 0.0735, 0.0738, 0.0739, 0.0742, 0.0744, 0.0748, 0.0751, 0.0754, 0.0757, 0.0759, 0.0762,
0.0764, 0.0767, 0.0771, 0.0774, 0.0778, 0.0780, 0.0784, 0.0787, 0.0790, 0.0792, 0.0795, 0.0798, 0.0802, 0.0805, 0.0810, 0.0816,
0.0819, 0.0824, 0.0830, 0.0837, 0.0843, 0.0848, 0.0854, 0.0862, 0.0867, 0.0874, 0.0881, 0.0888, 0.0896, 0.0903, 0.0910, 0.0916,
0.0922, 0.0930, 0.0938, 0.0949, 0.0958, 0.0970, 0.0984, 0.1005, 0.1030, 0.1077, 0.1154, 0.1339, 0.1710, 0.2300, 0.2851, 1.0000

=256(img 1)

**Table 3: Intensity values of CDF for img 2**

0.0001, 0.0001, 0.0001, 0.0002, 0.0004, 0.0007, 0.0015, 0.0024, 0.0033, 0.0041, 0.0051, 0.0059, 0.0068, 0.0074, 0.0085, 0.0094,
0.0104, 0.0114, 0.0126, 0.0135, 0.0146, 0.0157, 0.0166, 0.0179, 0.0196, 0.0209, 0.0227, 0.0235, 0.0245, 0.0254, 0.0268, 0.0276,
0.0284, 0.0294, 0.0301, 0.0308, 0.0315, 0.0320, 0.0327, 0.0334, 0.0336, 0.0342, 0.0347, 0.0350, 0.0354, 0.0357, 0.0358, 0.0361,
0.0366, 0.0368, 0.0371, 0.0375, 0.0377, 0.0381, 0.0385, 0.0389, 0.0393, 0.0396, 0.0400, 0.0403, 0.0405, 0.0407, 0.0409, 0.0411,
0.0413, 0.0413, 0.0419, 0.0421, 0.0424, 0.0426, 0.0428, 0.0430, 0.0433, 0.0436, 0.0439, 0.0442, 0.0443, 0.0446, 0.0448, 0.0449,
0.0452, 0.0453, 0.0454, 0.0456, 0.0457, 0.0459, 0.0462, 0.0465, 0.0466, 0.0468, 0.0468, 0.0470, 0.0471, 0.0473, 0.0473, 0.0474,
0.0475, 0.0477, 0.0477, 0.0479, 0.0480, 0.0482, 0.0484, 0.0485, 0.0486, 0.0488, 0.0491, 0.0492, 0.0493, 0.0495, 0.0497, 0.0498,
0.0499, 0.0500, 0.0502, 0.0502, 0.0503, 0.0504, 0.0505, 0.0506, 0.0507, 0.0509, 0.0509, 0.0511, 0.0514, 0.0515, 0.0516, 0.0517,
0.0518, 0.0519, 0.0520, 0.0521, 0.0522, 0.0524, 0.0526, 0.0528, 0.0530, 0.0532, 0.0532, 0.0533, 0.0535, 0.0537, 0.0538, 0.0540,
0.0541, 0.0543, 0.0545, 0.0547, 0.0549, 0.0552, 0.0554, 0.0556, 0.0558, 0.0560, 0.0563, 0.0566, 0.0569, 0.0571, 0.0574, 0.0576,
0.0578, 0.0580, 0.0582, 0.0584, 0.0587, 0.0590, 0.0592, 0.0596, 0.0600, 0.0603, 0.0607, 0.0610, 0.0612, 0.0615, 0.0618, 0.0621,
0.0624, 0.0625, 0.0628, 0.0630, 0.0633, 0.0637, 0.0639, 0.0643, 0.0645, 0.0648, 0.0652, 0.0654, 0.0658, 0.0661, 0.0663, 0.0667,
0.0671, 0.0673, 0.0676, 0.0678, 0.0682, 0.0685, 0.0687, 0.0691, 0.0695, 0.0696, 0.0699, 0.0702, 0.0705, 0.0708, 0.0713, 0.0718,
0.0720, 0.0724, 0.0727, 0.0730, 0.0734, 0.0736, 0.0740, 0.0743, 0.0747, 0.0750, 0.0755, 0.0758, 0.0761, 0.0763, 0.0768, 0.0772,
0.0776, 0.0780, 0.0781, 0.0785, 0.0788, 0.0791, 0.0797, 0.0801, 0.0806, 0.0811, 0.0817, 0.0822, 0.0827, 0.0831, 0.0837, 0.0844,
0.0853, 0.0863, 0.0873, 0.0888, 0.0903, 0.0920, 0.0941, 0.0974, 0.1014, 0.1072, 0.1190, 0.1441, 0.1833, 0.2289, 0.2787, 1.0000

=256(img 2)

**Table 4. Intensity values of CDF for img 7**

0.0001, 0.0001, 0.0001, 0.0001, 0.0001, 0.0002, 0.0002, 0.0003, 0.0004, 0.0005, 0.0006, 0.0007, 0.0009, 0.0009, 0.0011, 0.0012,
0.0015, 0.0016, 0.0019, 0.0021, 0.0023, 0.0025, 0.0028, 0.0029, 0.0031, 0.0033, 0.0035, 0.0038, 0.0040, 0.0041, 0.0043, 0.0044,
0.0046, 0.0049, 0.0050, 0.0052, 0.0053, 0.0057, 0.0061, 0.0065, 0.0067, 0.0068, 0.0071, 0.0075, 0.0079, 0.0081, 0.0083, 0.0086,
0.0092, 0.0096, 0.0112, 0.0119, 0.0124, 0.0133, 0.0141, 0.0149, 0.0157, 0.0164, 0.0169, 0.0175, 0.0182, 0.0189, 0.0197, 0.0202,
0.0206, 0.0213, 0.0220, 0.0226, 0.0232, 0.0237, 0.0245, 0.0249, 0.0255, 0.0260, 0.0266, 0.0272, 0.0277, 0.0282, 0.0299, 0.0309,
0.0314, 0.0322, 0.0329, 0.0336, 0.0342, 0.0346, 0.0351, 0.0357, 0.0363, 0.0366, 0.0372, 0.0377, 0.0382, 0.0389, 0.0395, 0.0400,
0.0404, 0.0409, 0.0417, 0.0423, 0.0429, 0.0433, 0.0439, 0.0445, 0.0451, 0.0458, 0.0465, 0.0470, 0.0475, 0.0479, 0.0485, 0.0489,
0.0493, 0.0502, 0.0508, 0.0514, 0.0520, 0.0525, 0.0530, 0.0534, 0.0538, 0.0548, 0.0553, 0.0564, 0.0570, 0.0575, 0.0580, 0.0584,
0.0588, 0.0592, 0.0595, 0.0598, 0.0601, 0.0606, 0.0612, 0.0616, 0.0620, 0.0624, 0.0629, 0.0634, 0.0638, 0.0643, 0.0646, 0.0652,
0.0655, 0.0660, 0.0663, 0.0666, 0.0670, 0.0675, 0.0678, 0.0682, 0.0686, 0.0691, 0.0694, 0.0700, 0.0705, 0.0709, 0.0713, 0.0719,
0.0723, 0.0728, 0.0733, 0.0738, 0.0744, 0.0748, 0.0753, 0.0755, 0.0761, 0.0771, 0.0780, 0.0785, 0.0791, 0.0797, 0.0802, 0.0806,
0.0810, 0.0816, 0.0820, 0.0824, 0.0828, 0.0830, 0.0836, 0.0840, 0.0845, 0.0848, 0.0852, 0.0857, 0.0863, 0.0868, 0.0872, 0.0878,
0.0882, 0.0887, 0.0895, 0.0899, 0.0905, 0.0909, 0.0913, 0.0919, 0.0924, 0.0929, 0.0934, 0.0941, 0.0946, 0.0950, 0.0959, 0.0965,
0.0969, 0.0974, 0.0986, 0.0990, 0.1003, 0.1010, 0.1017, 0.1022, 0.1028, 0.1034, 0.1039, 0.1047, 0.1054, 0.1060, 0.1066, 0.1073,
0.1081, 0.1086, 0.1093, 0.1101, 0.1107, 0.1115, 0.1123, 0.1131, 0.1138, 0.1148, 0.1158, 0.1168, 0.1179, 0.1188, 0.1212, 0.1222,
0.1237, 0.1247, 0.1263, 0.1277, 0.1293, 0.1305, 0.1322, 0.1336, 0.1358, 0.1374, 0.1407, 0.1449, 0.1534, 0.1798, 0.2387, 1.0000

= 256(img7)

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