International Journal of Technical Innovation in Modern Engineering & Science (IJTIMES)
Impact Factor: 3.45 (SJIF-2015), e-ISSN: 2455-2584
Volume 3, Issue 04, April-2017

Tongue print Analysis for colored images using MSE for Person Identification

Vibhooti Markandey[1], Jharna Chopra[2]

[1] Research Scholar, SSTC, SSGI, BHILAI, (C.G), INDIA
[2] Assistant Professor, SSTC, SSGI, BHILAI, (C.G), INDIA

Abstract

Tongue print of every Human is different and unique. Besides being unique it the least manipulated organ it enhances the security for identification and authentication of a person avoiding mostly occurring forgery cases. Taking colored image for the study itself over shades the limitations of inaccurate or not up to the mark results. The paper considers colored pixel analysis using the technique of Mean Squared analysis (MSE). The technique employs pixel-by-pixel analysis of the image and extracting the matching criteria. Since every pixel is considering for the extracting the feature it assures more accuracy of the results.

Keywords

Biometrics, Tongue Print, colored pixel, MSE.

1. Introduction

So far, there had been various developments in the field of person Identification and authentication. Biometrics developed a Single-modal (Fingerprint, Irish, Footprint, Face, Etc.) and multimodal (Combination of one or more Modalities) approach to for the same. Multimodal definitely over shading the loopholes of system single modality but itself left with own flaws.

On the other hand, we can discuss a unique feature of human body – tongue Print for person identification. Adding another level of accuracy to person identification and authentication the paper communicates a new technique i.e. Tongue print analysis. The analysis follows the traditional sequence of identification steps for the study:

- Image acquisition
- Image manipulation
- Database creation
- Feature extraction
- Matching
- Decision making

Following the setup though non-peculiar tongue prints of various persons have been captured. For preparing the database, they are stored with a common specifications and scale. The Tongue image is thus enrolled as the ID given to individual image.Enrolled images are thus preprocessed to highlight the unique features of tongue. Just like the uniqueness of physiological features of various modalities of biometrics, Tongue Print of a person possesses uniqueness in itself. Tongue print of every Human is different and unique in this it has various traits. First, it has geometric feature with texture, which are unique and invariant for an individual. Second, the only internal organ is easily accessible for study. Third, it is the least manipulated organ, which enhances the security of identification, avoid mostly occurring forgery cases. Last, the involuntary squirm of the human tongue not only is a natural and convincing proof that a subject is alive, but it also be utilized for discriminating individuals[1]. The paper consider colored pixel analysis using the technique of Mean Squared analysis (MSE). The technique employs pixel-by-pixel analysis of the image and extracting the matching criteria. Since every pixel is considering for the extracting the feature it assures more accuracy of the results.

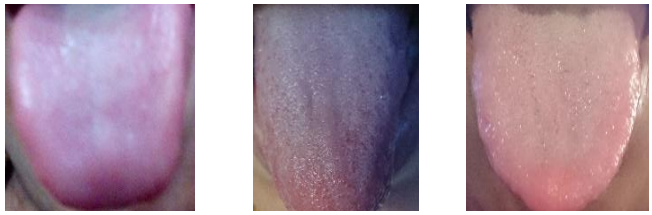

Fig. 1. Some sample Tongue.

Following sections explain the whole process in section 2 few related researches are discussed in section 3 the tongue feature extraction is explained. Section 4 proposes the Methodology employed where we acquire the interest points of images or a part of image for the comparison between the two. Giving an outlook to the study section 5 reflects the results finally section 6 provides the conclusion and future scope of the study.

2. **Literature review**

Making a way for a novel biometrics identifier, a dynamic tongue print identifier was introduced which uses both static and dynamic feature of the biometric [1]. Finding point of correspondence between two images is one of the methodology for object recognition. As mentioned earlier there had been many physiological and behavioral aspects of biometrics had been implemented viz. face [2,3], iris [4,5], finger-print[6], palm-print [7], foot-print and gait [8], voice [9] and signature [10].However, they are ineffective in combating identity fraud[11]. The multimodal Biometrics Study at different point of concern shows the importance of having a common baseline system for benchmarking of fusion level [12]. Nevertheless, pertaining the quality of least gullible tongue hold the dynamic feature for the study. The system implementing this with physiological and neural study describe crucial role of dynamic information in the human visual recognition process [13].The finding of point of correspondence involves the two-way process detection of interest point also the description of interest point. Based on the Eigen values of the second moment matrix, Harris corner detector is probably most widely used [14].Lindeberg [15] automatic scale selection allows selecting interest point with their own characteristics.A variety of descriptor had been introduced viz. Gaussian [16]. In context to Pixel analysis of images is incorporated at different prospect for which different image enhancement techniques by using their quality parameters (MSE & PSNR) is used and new erosion enhancement technique were established[17].

3. **Preprocessing**

The preprocessing for the work starts with building a database. The speculation is general, like other modalities of biometrics i.e. capturing and storing the data with and enrolled identification abbreviations. The other concern for preprocessing is to discuss the feature of tongue. The distinct patterns are observed of the tongue print during the study. Here we collate few tongue print based on Region of Interest (ROI). Since the pixel-by-pixel analysis is considers the ROI are extracted from different coordinates of the image. These ROI been thus incorporated for matching to the training image thus passing the criteria for the test image set. The following image shows the different ROI.

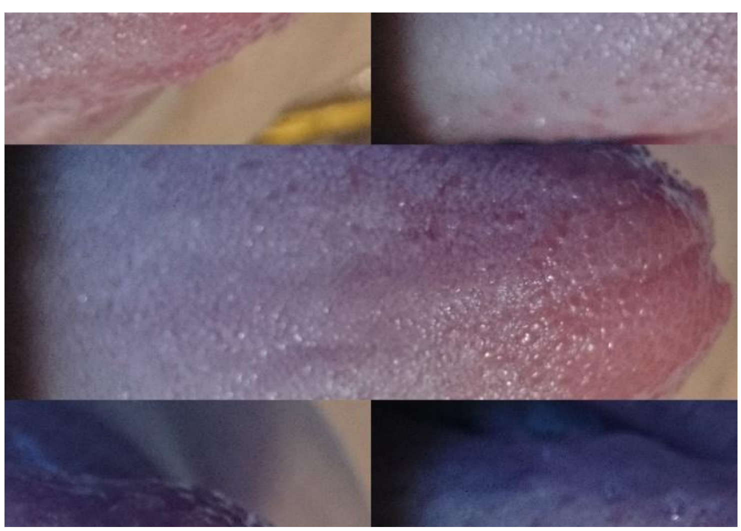

Fig.1. ROI from different quadrants.

For further pre-processing we consider an input from the enrolled images in .jpeg format.

4. Methodology

The methodology can be depicted in the form of a flow diagram. To begin with the process it describes the acquisition of image. Image manipulation will convert into appropriate format, finally the image will compared using MSE and the comparative result will be generated. Fig. 3 is the Block diagram for framework followed in the study.

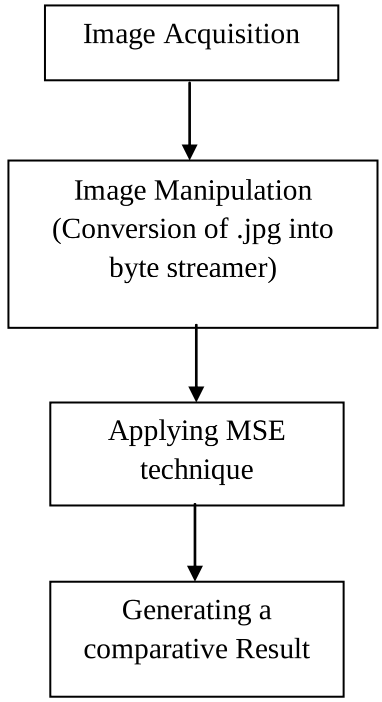

Fig.3 Block diagram representing the workflow

4.1 Image Acquisition

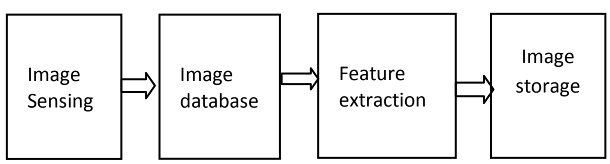

Fig.4 Steps for mage acquisition

The fig.4 shows the steps for the acquisition of image an enrolment of the image for training database. Though no peculiar setup has been followed for illumination management but use of some kind of diffuse illumination either in the form of a high number of less-powerful light sources or by illuminating a rough surface which then reflects the light (randomly) toward the tongue image is desired.

4.2. Image manipulation

Here the .jpeg image is converted into byte streamer. Those byte streamer extract the colours from individual pixels of acquired image. Progressing the processing into the estimation of mean squared error. The MSE compare the image pixel by pixel and generate the matching parameters for the Training and Test data.

4.3 Mean squared Error (MSE)

Let X1, X2,……, Xn be n random variables, i.e., a random sample from f (x|θ), where θ is unknown. An estimator of θ is a function of (only) the n random variables, i.e., a statistic θ = r(X1,……., Xn). There are several methods to obtain an estimator for μ, such as the MLE, method of moment, and Bayesian method. A difficulty that arises is that since we can usually apply more than one of these methods in a particular situation, we are often face with the task of choosing between estimators. Of course, it is possible that different methods of finding estimators will yield the same answer, which makes the evaluation a bit easier, but, in many cases, different methods will lead to different estimators. We need, therefore, some criteria to choose among them. We will study several measures of the quality of an estimator, so that we can choose the best. Some of these measures tell us the quality of the estimator with small samples, while other measures tell us the quality of the estimator with large samples. The latter are also known as asymptotic properties of estimators.

4.2.2 Mean Square Error (MSE) of an Estimator

Let $\hat{\theta}$ be the estimator of the unknown parameter μ from the random sample X1,X2,……,Xn. Then clearly the deviation from $\hat{\theta}$ to the true value of θ, $|\hat{\theta}- \theta|$, measures the quality of the estimator, or equivalently, we can use for the ease of computation. Since $\hat{\theta}$ is a random variable, we should take average to evaluation the quality of the estimator. Thus, we introduce the following

Definition: The mean square error (MSE) of an estimator $\hat{\theta}$ of a parameter θ is the function of θ defined by, and this is denoted as MSE$\hat{\theta}$. This is also called the risk function of an estimator, with $(\hat{\theta}- \theta)^2$ called the quadratic loss function. The expectation is with respect to the random variables X1, X2,……, Xn since they are the only random components in the expression. Notice that the MSE measures the average squared difference between the estimator $\hat{\theta}$ and the parameter θ, a somewhat reasonable measure of performance for an estimator. In general, any increasing function of the absolute distance $|\hat{\theta}- \theta|$ would serve to measure the goodness of an estimator (mean absolute error, E $(\hat{\theta}- \theta)$, is a reasonable alternative. But MSE has at least two advantages over other distance measures: First, it is analytically tractable and, secondly, it has the interpretation.

$$MSE\,\hat{\theta} = E\big(\hat{\theta} - \theta\big)2$$
$$= V\,ar(\hat{\theta}) + \big(E(\hat{\theta}) - \theta\big)2$$
$$= Var(\hat{\theta}) + (Bias\ of\ \hat{\theta})2 \qquad (1)$$

This is so because

$E\big(\hat{\theta} - \theta\big)^2 = E(\hat{\theta}^2) + E(\theta^2) - 2\theta E(\hat{\theta})$

$= Var(\hat{\theta}) + [E(\hat{\theta})]^2 + \theta^2 - 2\theta E(\hat{\theta})$

$= Var(\hat{\theta}) + [E(\hat{\theta}) - \theta]^2$(2)

Definition: The bias of an estimator $\hat{\theta}$ of a parameter θ is the difference between the expected value of $\hat{\theta}$ and θ; that is, Bias$(\hat{\theta})$ = E$(\hat{\theta})$- θ. An estimator whose bias is identically equal to 0 is called unbiased estimator and satisfies E$(\hat{\theta})$ = θ for all θ. Thus, MSE has two components, one measures the variability of the estimator (precision) and the other measures the its bias (accuracy). An estimator that has good MSE properties has small combined variance and bias. To find an estimator with good MSE properties, we need to find estimators that control both variance and bias. For an unbiased estimator$\hat{\theta}$, we have:

$$MSE\hat{\theta} = E(\hat{\theta} - \theta)2 = Var(\hat{\theta})(3)$$

Therefore, if an estimator is unbiased, its MSE is equal to its variance.

The simulation to evaluate MSE will take the training data from the training data set and from test data set. Fig.5 interface represents the simulation window for the comparison.

Fig.5 Simulation window

5. Results

The final step is decision-making is how the test data is matched to the training data. Here we have defined few parameters for depicting the observed results:

1. Percentage of similarity
2. Number of pixel matched
3. Number of pixels varied
4. Comparison time

The simulation considers taking an image and comparing with test image which could be the segment of the image or any differed image. The percentage similarity will give the percentage the number of pixels matched of test image to that of training image. The number of pixel matched will be plot. The plot will depict the comparison time. We can observe this point in the form of a bar chart. Fig.6 represents the bar chart for different parameters.

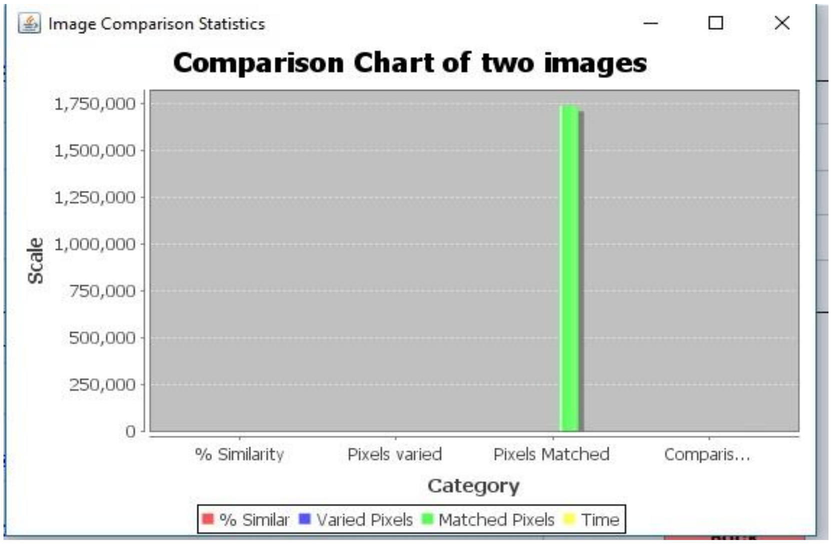

Fig.6 Comparison Chart of two images

6. Conclusion and future scope

The tongue pattern detection is one of the key point for the biometrics study. Considering tongue as one of the parameter for person identification is the goal of the study. Alternatively, we have achieved the feasible matching of images Using Mean squared error detection in colored pixel of the tongue images. On the verge of seeking accuracy, the images to be analyzed using different filters. As mentioned earlier the symmetry is still the key measure for further implementation. To reach at higher level of accuracy we can observe the tongue print analysis in RGB scale of image the live detection from the involuntary squirm of tongue promoting the accuracy to it. Considering the broader aspect of study of Tongue votes for its induction as a biometric parameter.

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