Kernel Approach for Similarity Measure in Latent Fingerprint Recognition

Sachin Kumar
Department of Computer Science and Engineering
National Institute of Technology Tiruchirappalli-620015
Tiruchirappalli, India
E-mail: 306111053@nitt.edu

R. Leela Velusamy
Department of Computer Science and Engineering
National Institute of Technology Tiruchirappalli-620015
Tiruchirappalli, India
E-mail: leela@nitt.edu

***Abstract*- The Recognition of Fingerprint is one of the fundamental problems in the field of pattern recognition. Unfortunately, accuracy of Latent fingerprint matching is still difficult implication and challenging until today. To find the similarity between two images is a trivial task. This process becomes more challenging and risky, when among two input images one is poor quality, such as a latent fingerprint. Latent fingerprints are distorted, partial and having background noise. The main motto of this research is to design an intelligent procedure equivalent to human perception in matching the latent to exemplar fingerprint scenario. In this paper, a new Kernel-based structural similarity measure algorithm is designed for match score computation. The proposed approach is more robust to invariance such as scale change and rotation in the input image. The result describe, that the similarity score value is improved by 1.6% on an average as compared to existing similarity calculation approach.**

Keywords: Latent fingerprint; Kernel method; Log-polar transform; Similarity measure: Learning approach.

I. INTRODUCTION

This Human identification based on latent fingerprint has been widely used by law enforcement organization to confirm the identity of the suspected criminal. Latent fingerprints are the ridge impressions left unintentionally on the surface of an object. Later these prints are collected using some chemical process and kept in a file for further process. A latent fingerprint is the major source of evidence to append the criminal by matching an unknown print to known print database using state-of-the-art mechanism such as Integrated Automatic Fingerprint Identification System (IAFIS) [1-2]. Due to poor quality and non-linear distortion in latent image, latent fingerprint matching is one of the risky concepts in pattern matching literature. Since latent fingerprint has very few numbers of minutiae features as compared to exemplar fingerprint. On an average, a latent fingerprint has only 21 minutiae while exemplar fingerprint has 106 minutiae [3]. To convict the match with such a less number of feature values is one of the biasing questions in forensic science community [4-5]. The goal of this research is to design an intelligent computing system for low-quality image recognition. Since a machine intelligence equivalent to human perception is the main focus of current research trend [6-8]. A specific mechanism should be designed in a modular fashion using advanced machine learning algorithms. As human brain learn the information piece-wise and capable of perceiving the error by using previous activity knowledge from its brain neuron signals [9-10]. For example, FBI-NGI (Federal Bureau of Investigation - Next Generation Identification) project focused on light-out mode [8]. The design of such advanced and intelligent learning capability system is possible only if it is done in a piece-vise manner.

Fundamentally, the fingerprint has three main steps for its recognition (as shown in Table 1): preprocessing, feature extraction, and matching. Exemplar fingerprints have sufficient features to match with another exemplar fingerprints to identify the similarity between two fingerprints. In the case of latent fingerprint, matching with the exemplar fingerprint is a demanding process. A more advanced and intelligent preprocessing steps is required to extract the sufficient features to distinguish them. Dictionary based learning techniques for preprocessing has given immense success to improve the latent fingerprint clarity [8]. This technique is based on supervised machine learning and it uses the good quality orientation patch to correct the distorted orientation in the latent fingerprint image enhancement.

Table 1**:** Various stages during Latent Fingerprint recognition

Steps/Stages	Function/Process	Learning approach
Preprocessing [8]	Image Enhancement	Supervised learning
Feature Extraction [6]	Intelligently automatic feature markup	Supervised and semi-supervised learning approach
Matching [4]	Kernel based Similarity measure	Semi-supervised or Unsupervised

The design of learning based feature extraction is a recent advancement in the fingerprint research. The main goal of feature extraction process is to differentiate between minutiae and non-minutiae output for input latent fingerprint in an advanced fashion [6]. This process used spectral de-noising neural network technique to design good quality patches. These patches will differentiate minutiae and non-minutiae in latent fingerprint.

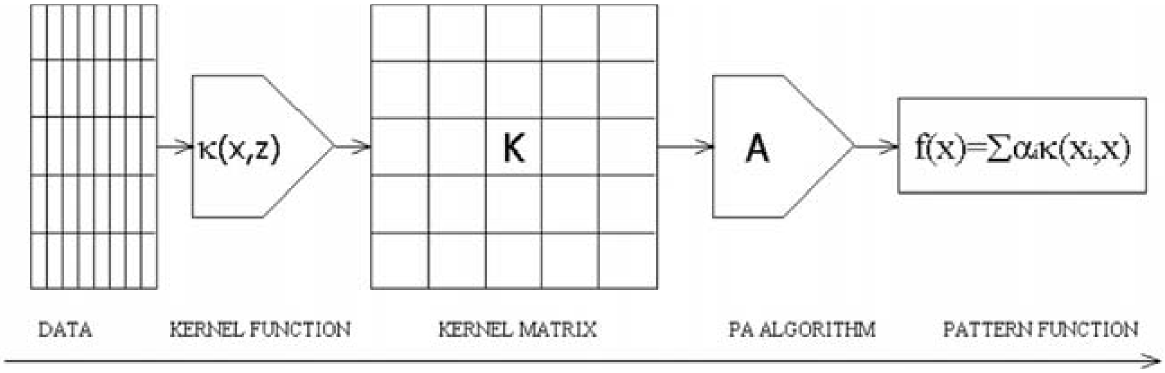


Fig. 1 General framework for various stages used in kernel based approach [18].

In fingerprint matching, feature alignment and match score computation is one of the biggest problems [4]. Numerous algorithms have been proposed to calculate the similarity score for fingerprint matching. In recent years, kernel has been a dominating area of research in various pattern recognition and computer vision application [18]. Due to its remarkable success and accuracy in various applications, the kernel-based machine learning concept is introduced to match latent fingerprints. Fig.1 is the Sketch of a modular inherent of a kernel based algorithm. Data is transformed into a kernel matrix using K function, then pattern analysis algorithm uses this information to find the suitable relation as a linear combination of kernel function.

In this paper, a new kernel is designed to calculate the similarity score for low quality fingerprint recognition. The organization of the paper is as follows: Section 2 describes the motivation behind the proposed algorithm. In section 3, a literature review is carried out on similarity score calculation mechanism and various concept evolution for algorithm design is given in Table 2. Section 4 describes the kernel based similarity score calculation mechanism for latent fingerprint matching. In section 5, experiment and result analysis is given to prove, and to check the functionality of the proposed mechanism on publically available datasets NIST SD27. Finally last section describes the conclusion and further research direction.

II. Motivation

To find the similarity between two images is immensely important in many application areas from object recognition (e.g., medical image analysis, moving object recognition in video, Surveillance camera, GIS, etc.) to big data analysis. Latent fingerprint recognition is one of the provoke procedure in the pattern recognition field. To design a system having perception equivalent to human intelligence is the goal of current research scenario and it is very attractive field of research [9]. To apply machine learning algorithm in different module is the best solution for latent fingerprint recognition problem. Human brain learns the information in a peace-vise manner. Similarly the kernel has been designed in such a way that it calculates the score like human brain. Latent fingerprint matching faces the challenge in term of scale change and rotation. This was the motto to propose a solution to find the similarity score, which is invariant of rotation and scale change [10].

III. Literature Review

There are large numbers of algorithms proposed till now to match the fingerprint [12]. Based on the literature study, similarity measure algorithm has been categorized as follows:

1. *General algorithms:* These algorithms are based on basic concept of pixel wise matching that is applicable to good quality image matching scenario (sequential combination). These methods find the similarity of visual patterns between two images pixel-vise. Sparse data processing is a major issue in matching [21].

2. *Feature-based:* Feature-based algorithms are developed in three stages: First one is global similarity score. It uses global features such as type of pattern, orientation field, and frequency field. Second one is Local similarity score, which uses fine level detail of fingerprint to find the match. Finally, third stage is a combination of above both stages known as the hybrid stage. A global feature is used as a clue by utilizing neighboring information to match the fingerprint image more accurately [15] [17].

3. *Distance-based:* Distance and similarity are dual concepts because they work bijectively to induce a similarity score. It matches more positively, if distance metric measured by Euclidian formula satisfies (based on angular and spatial measurement) with some possible variation. Euclidian–distance is used to store distance of nearest neighborhood minutiae as additive features in distance-based matching algorithms [13].

4. *Probabilistic measure:* Bayesian analysis is main idea to find the probability of next feature to assure a genuine match score. It helps to calculate the rare feature accuracy for suitable match score computation. Latent fingerprint have very few number of level-1 and level-2 features to identify these prints uniquely [4]. Rare feature such as level-3 have the capability to match latent fingerprint with more confirmation. Latent fingerprint have minimum feature and includes rare features to find the maximum score to assure a reliable match [16].

Table 2: Historical evolution of similarity measure algorithm developed for fingerprint matching algorithms

Sl. No.	Algorithm	Concept used	Description	Challenge
1.	Basic property of Image processing [21]	General approach	Use basic concept of pixel-vise Image processing and recognition	Sparsest image is one of biggest challenge: Not used to process unused points
2.	Singular-point and minutiae [15], [17]	Feature-based concept	Use spatial feature in form of minutiae(ridge ending/bifurcation and ridge orientation)	Individuality: how many feature are sufficient to identify uniquely
3.	MCC, Descriptor based match [13]	Distance-based method	Euclidian distance is used to keep track distance metric between neighbor minutiae	Distortion and noise can create variation in measurement
4.	Quantitative analysis [4]	Probabilistic approach (Biasing: feature marks on same fingerprint by different expert)	Bayesian analysis concept is used to match rare feature such as dots or incipient ridge with more confirmation to resolve biasing.	Latent fingerprint recognition with few number of feature
5.	Advance approach [9],[10]	Learning-based techniques	Uses advance learning base methods such as kernel approach	Extra computation cost

5. *Advanced algorithms:* These algorithms are based on current learning based algorithms for fingerprint matching. It is well known fact, that machine preservation accuracy as compared to human is low. With the advancement of machine learning based algorithms, it is possible to perceive the image equitant to human perception. These algorithms are used in various applications such as medical image analysis, GIS, moving object recognition, etc. This research is the outcome of such an advanced learning based approach. [9-10].

IV. Proposed Work

The similarity between two good quality image can be determined easily, but this process becomes more complex and difficult when one of the two input image is of very low-quality such as latent fingerprint. In latent fingerprint recognition, a similarity measure is calculated in such a way that it selectively identify the individual patterns, which are invariant in scale and position of context. Selectivity of these patterns is used to design similarity algorithm equal to human perception [12]. In this paper, kernel based approach is introduced for identifying a pattern in latent fingerprint matching with exemplar. A kernel is an inner product space, defined by neural response of natural image representation [18]. By considering a complex feature representation and pooling match score computation mechanism, a specific kernel is designed for each image to find better match score with advanced error control features like human visual cortex [16].

A. Basic Idea of Kernel

Kernel is a unified and powerful framework for the general type of data, e.g., text, vector, strings, etc. It provides an efficient way to find the relation in a non-linear pattern of data using kernel-based algorithms. Kernel makes the generic entity with important algebraic tools to calculate robust similarity score by considering suitable norms of scaling in feature space [18]. It leads to predict more accurate feature selection by embedding the kernel function in data and help in calculating the good score to match the distorted part with more accuracy. Kernel model can perceive the similar pattern like human brain by decomposing the image into different patch size. The model is design in a local hierarchical bottom up fashion. In this paper for the simplicity of process, only three layers *u*, *v*, and *sq* with $u \subset v \subset sq$ are composed of three patches. For a grey scale image of size *sq* is the function describe by the image patch I_{sq}. In the same way I_u and I_v can be defined by *u* and *v* patches as shown in Fig. 2. The low layer contains the sets of sub image patches I_u, middle layer consist set of image patches I_v, and complete image is the top layer patch I_{sq}.

Distortion in latent fingerprint is limited to change in shape due to transformation of two adjacent patches. Let H_u and H_v be the set of translation for moving window of size *u* and *v* in patch *v* and *sq* respectively as shown in Fig. 3. Note that, step length may be more than one pixel depend on location and gap between two consecutive ridge in given domain. For example image patch g'_{11} obtain as $g_{21} \circ h^{v}_{11}$ by moving the patches I_u on corresponding super patch I_v, where $\circ$ is restriction for translation. Finally, the templates t^u and t^v are for the neurons at different level of visual perception respectively and form a kernel map score matrix to calculate the best match patch in form of a neural response vector.

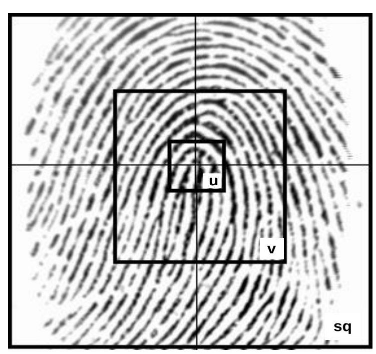


Fig. 2 Domains of nested patch

B. Design Concept

Design procedure for the kernel in a bottom up fashion:

1. The computation begins with the calculation of non-negative normalized reproducing kernel on $I_u \times I_u$ patch denoted by $\widehat{K}_u$(g', t^u), where $g' \epsilon I_u$ and $t_u \epsilon T_u$. For simplicity linear kernel can be chosen:

$$K_u(g', t^u) = \langle g', t^u \rangle \,. \quad (1)$$

$$\widehat{K}_u(g', t^u) = \frac{K_u(g', t^u)}{\sqrt{K_u(g', g')K_u(t^u, t^u)}} \quad (2)$$

Note: image patches having no pattern are ruled out, or if $K_u(g', g') = 0$ and $K_u(t^u, t^u) = 0$. $\widehat{K}_u$(g', t^u) is generated normalized kernel matrix of similarity score map between template t^u and for all patches element of input sub image set I_u. The maximum match template score is calculated using the neural response (eq. 3) for each kernel value. The score is stored in a vector for the input patches of element I_u by finding the appropriate invariance (translation) parameter with the help of corresponding patch I_v.

2. Neural response for the first layer at t^u of $g \epsilon I_v$ is describe as:

$$N_v(g)(t^u) = \max_{h^u \epsilon H_u} \widehat{K}_u(g * h^u, t^u) \quad (3)$$

In the image patch g, $g * h^u \epsilon I_u$. $N_v(g)(t^u)$ is the best match for template t^u . For the coordinates value $N_v(g)(t_i^u)(i = 1,2, \dots, |T_u|)$ the neural response of g is calculated as a vector in $R^{|T_u|}$. Where $|T_u|$ is the size of template set T_u. So

$$N_v(g) = \begin{pmatrix} N_v(g)(t_1^u) \\ N_v(g)(t_2^u) \\ \vdots \\ N_v(g)(t_{|T_u|}^u) \end{pmatrix} \quad (4)$$

It is easy to find the first layer neural response for each image patch $g_{ij} \epsilon I_v$.

3. Based on above calculation the derived kernel on $I_v \times I_v$ as

$$K_v(g, t^v) = \langle N_v(g), N_v(t^v) \rangle \quad (5)$$

Where $t^v \epsilon\, T_v, g \epsilon I^v$ and $\langle .,. \rangle$ is L^2 inner product [18]. $K_v(g, t^v)$ can be normalized as eq. 2 to obtain $\widehat{K}_v(g, t^v)$. The derived kernel for each image patch size *v* and templates T_v, can be finds by the given step.

4. By following the above process in the same way the second layer neural response

$$N_{sq}(f)(t^v) = \max_{h^v \epsilon H_v} \widehat{K}_v(g * h^v, t^v) \quad (6)$$

Where, $f \epsilon I_{sq}$ and $t^v \epsilon T_v$. Consequently the kernel derived for $I_{sq} \times I_{sq}$ is given as

$$K_{sq}(f_1, f_2) = \langle N_{sq}(f_1), N_{sq}(f_2) \rangle \quad (7)$$

Where $f_1, f_2 \epsilon I_{sq}$. In the same scenario $\widehat{K}_{sq}$ can be computed. $\widehat{K}_{sq}$ is the similarity measure between f_1 and f_2. Note, the above computation can be done up to n layer architecture [10].

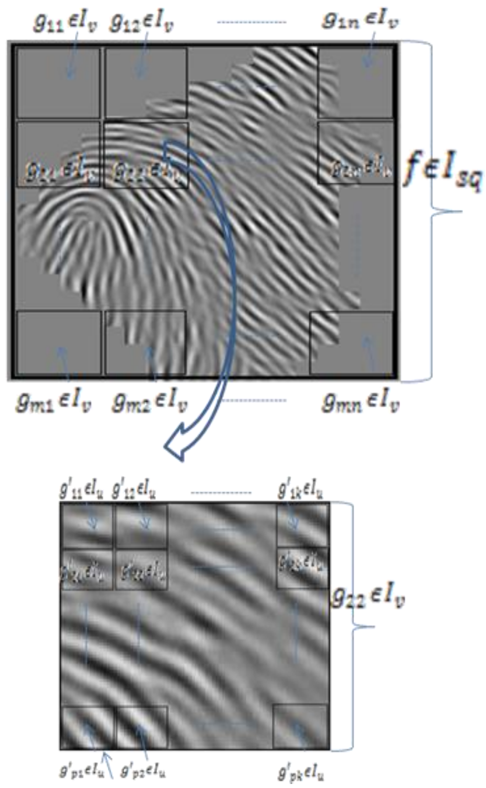


Fig. 3 Image patches on different layer and their sub-patches

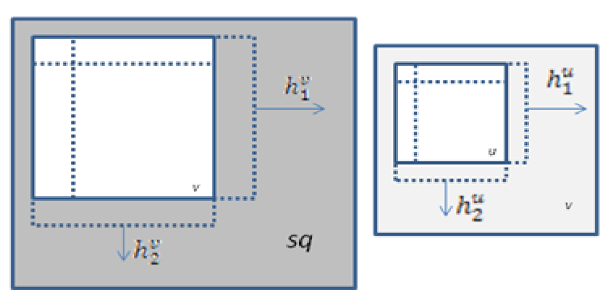


Fig. 4 Translation in *sq* (left) and *v* (right)

C. Algorithm

Design procedure for the proposed Kernel based similarity algorithm for latent fingerprint recognition is as follow:

Input: Images f_1 and f_2
Output: K^_sq

1. For input latent and match image, center points are denoted as (x_0, y_0). It is calculated using state of art pose estimation algorithm [19].
2. The log polar transform image $L(f_1)$, and $L(f_2)$ are produced for non-uniform image using sampling method. This procedure is use to convert image from Cartesian coordinate to log polar coordinate with coordinate x and y, by Using the equation $x = \rho \cos\theta + x_0$, and $y = \rho \sin\theta + y_0$.
3. Then compute the neural response for second layer of log polar image $N_{sq}(L_1)$ *and* $N_{sq}(L_2)$.
4. Finally the output is kernel based similarity score $\hat{K}_{sq}(L(f_1), L(f_2))$.

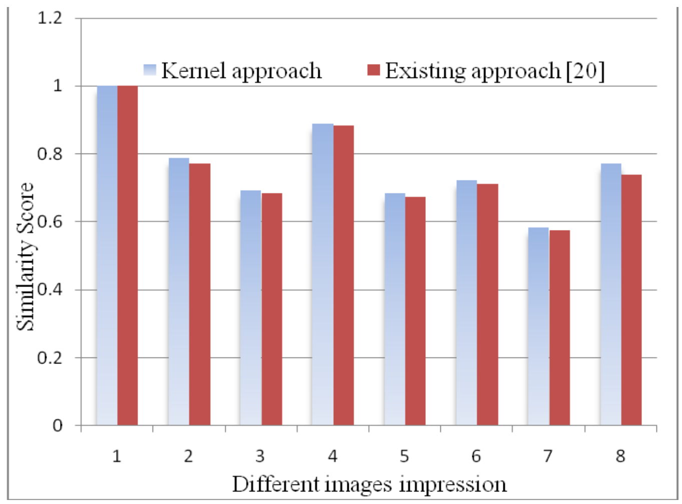
Invariance property to rotation and scale for image patch in R^2 can be defined as:
For any change $r \epsilon R$ and for every $h^v \epsilon H_v$ at log polar plane, the relation hold true if $L(f) * h^v = L(f * r) * \tilde{h}^v$.
Where, $\tilde{h}^v$ is translation at the log-polar plane and for any given image f, the rotation invariance.
$N_{sq}(L(for)) = N_{sq}(L(f))$, for all $r \epsilon R$.

V. Experimental Result and Analysis

In this section, result in context of similarity measure for latent fingerprint matching is presented with improved accuracy. The above hypothesis is implemented in MATLAB 2012 and verified on NIST SD27 and FVC2002 low quality fingerprint dataset. Based on the experimental results with the help of newly developed kernel based matching approach, the performance is improved with extra computation cost. Table 3 describes the analysis of similarity score for low quality fingerprint with different impression for same image. In our experiment one image is taken as it is to check the score for same impression. The comparison of similarity score for proposed and existing approach [20] is shown in Fig. 5. Fig. 5 states that, the average similarity score of proposed kernel based approach is 1.6% more than existing approach. Based on the result, the proposed similarity score calculation gives better score as compared to existing approach. The experiment is performed on given B_157 image from NIST SD27. These images are enhanced using global and local dictionary [7-8] and the similarity score on dataset of enhance image is calculated. Where image Sr. No. 1-8 are FVC images and image 9-10 are NIST SD27 bad quality image. It gives the 0.04002 increment in similarity value.

Table 3 Analysis of Similarity score for propose and existing approach on FVC and NIST SD 27 images.

Sr. No.	Kernel approach	Existing approach [20]	Increase	% change
1	1	1	0	0
2	0.7883	0.77076	0.022757	2.275676
3	0.6934	0.68476	0.012618	1.261756
4	0.8893	0.88396	0.006041	0.6041
5	0.6853	0.6742	0.016464	1.646396
6	0.7223	0.71263	0.013569	1.356945
7	0.5836	0.5766	0.01214	1.214013
8	0.773	0.73983	0.044835	4.483462
9	0.6423	0.60228	0.04002	4.002
10	0.6313	0.55130	0.07685	7.685
Average score for Similarity Using Kernel Approach				1.605294



VI. Conclusion and Future Work

This work proposed a new approach for Similarity measurement in latent fingerprint matching. Matching low quality image to exemplar image is one of the provoke method in recognition literature. To calculate the similarity with very few minutiae in latent fingerprint image is not reliable. To make this procedure more robust, a function like kernel is necessary. Kernel controls the erroneous features confirmation during matching score calculation. The result presented in section V proves the robustness of proposed solution for similarity score calculation. In case of distortion (change in image shape), above method give better score than existing approach. In future, testing of proposed concept will be carried out on different dataset and more challenging environment like live video analysis.

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