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Efficient Fingerprint Recognition System Using Pseudo 2D Hidden Markov Model

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Abstract: Fingerprint can only uniquely identify a person when compared to other types of biometric features. The existing system used the combination of bayes classifier and Henry classifier to increase the speed of authentication process and to provide accurate classification system, respectively. But the combination of those classifiers in real time systems becomes difficult to implement. This fingerprint recognition system uses the pseudo 2D hidden Markov Model which considers each types of fingerprint as separate states with different levels of Markov chain. During the recognition process, the Markov Model verifies each super states to identify which types of fingerprint, then it can match the given fingerprint image with the image which are kept in database. The proposed research will improve the speed and recognition rate by using the pseudo 2D hidden Markov Model.

Key words: Fingerprint recognition, Pseudo 2D Hidden Markov Model, fingerprint classification, authentication, database

INTRODUCTION

The most of real time systems prefer that fingerprint as an efficient biometric feature to uniquely identify an authorized user. A fingerprint has unique texture structure to describe orientation field of fingerprint images. A fingerprint has the different orientation angle structure in different local area of the fingerprint and has a texture pattern correlation among the neighboring local areas of the fingerprint (Gu *et al*., 2006). The different samples selected from the same fingerprint are very similar and obey a statistical probability distribution. The fingerprint matching based on statistical approaches is usually insensitive to the quality of fingerprint images.

A fingerprint recognition system recognizes a person's identity by comparing the captured fingerprint with his/her own previously enrolled reference template stored in the database (Leung and Leung, 2011). It conducts a one to many comparison to confirm whether or not the claim of identity by the individual is true.

Fingerprint consists of number of lines which flow in different directions is called ridges and the gap between those ridges is known as valleys. A fingerprint pattern can be categorized according to their minutia points such as ridge ending, bifurcation, core, delta and cross over that are depicted in Fig. 1. A ridge ending is a minutia point where a ridge terminates. A single ridge path is splitted into two paths (Maltoni *et al*., 2003). A center point of the fingerprint pattern is known as core. A singular point from which three ridges deviate is called as delta (Li and Kot, 2011). This core and delta locations can be used to match two fingerprints.

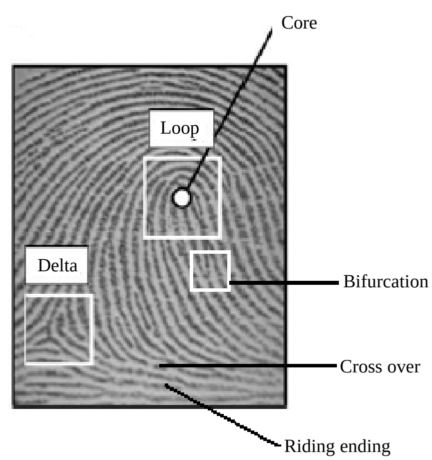

Fig. 1: Fingerprint minutiae-points

Fingerprints can be matched by one of two approaches such as minutia matching and global pattern matching (Lumini and Nann, 2008). In minutia matching, each minutia is matched with above mentioned minutia points. In global pattern matching, the global pattern (Gu *et al*., 2006) of fingerprint consists of six patterns: arch, tented arch, right loop, left loop, whorl and

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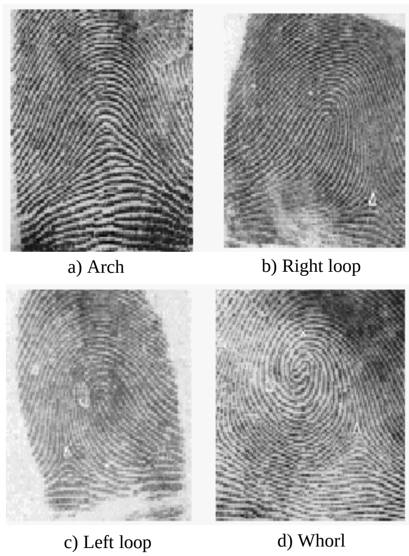

Fig. 2: Types of fingerprint a) arch, b) right loop, c) left loop and d) whorl

twin loop. But the enhanced fingerprint recognition process consider the four major categories like arch, right loop, left loop and whorl (Fig. 2) as the super states of pseudo 2D hidden Markov chain (A Hidden Markov Model Fingerprint Classifier, Andrew Senio). The tended arch and twin loop categories of fingerprint are considered as sub states of arch and whorl super sates, respectively. Each pattern can be compared by the flow of ridges between two fingerprint images.

A fingerprint texture with specified details changing across a predefined path on the finger surface can be viewed as a Markov chain as in (A Hidden Markov Model Fingerprint Classifier, Andrew Senio). Hidden Markov Model (HMM) is expected to be an efficient approach in fingerprint matching, since it has been successfully applied to speech recognition and other recognition systems (Kant and Nath, 2009).

Andrew Senior presented a HMM approach in fingerprint classification and verified that the HMM approach is effective (Kant and Nath, 2009; Senior, 1997). Andrew Senior's approach uses a number of fingerprint parameters which are related to ridge details. Those ridges were extracted only after smoothing and thinning processes and that is time consuming.

LITERATURE REVIEW

The Fingerprint Authentication System (FPAS) used the combination of bayes classifier and Henry classifier to increase the speed of authentication process and to provide accurate classification systems, respectively (Parvathi and Sankar, 2012). The earlier research degrades its performance by complex combination of those classifiers in real time systems.

Leung and Leung (2011) proposed a method to recognize the fingerprint image with the help of bayes classifier. Even though it overcomes the problem of one to one matching and slow retrieval of image, it does not have the Henry classes to improve consistency problem (Prabhakar, 2001) and used only one sample per finger which degrades accuracy of the system.

Gu *et al*. (2006) proposed a method for fingerprint verification which includes both minutiae and model based orientation field is used. It gives robust discriminatory information other than minutiae points. Fingerprint matching is done by combining the decisions of the matchers based on the orientation field and minutiae.

Girgisa *et al*. (2007) proposed a method to describe a fingerprint matching based on lines extraction and graph matching principles by adopting a hybrid scheme which consists of a genetic algorithm phase and a local search phase. Experimental results demonstrate the robustness of algorithm.

Ji and Yi *et al*. (2008) proposed a method for estimating orientation field by neuron pulse coupled neural network and block direction by projective distance variance of a ridge.

Lumini and Nann (2008) developed a method for minutiae based fingerprint and its approach to the problem as two class pattern recognition. The obtained feature vector by minutiae matching is classified into genuine or imposter by support vector machine resulting remarkable performance improvement.

Mohamed presented Fingerprint Classification System using fuzzy neural network. The fingerprint features such as singular points, positions and direction of core and delta obtained from a binaries fingerprint image. The method is producing good classification results. Prabhakar (2001) has developed filter-based representation technique for fingerprint identification. The technique exploits both local and global characteristics in a fingerprint to make identification. The matching stage computes the Euclidean distance between the template finger code and the input finger code. The method gives good matching with high accuracy.

The proposed Fingerprint Recognition System uses the pseudo 2D hidden Markov Model which considers each types of fingerprint as separate states with different levels of Markov chain. During the recognition process, the Markov chain verifies each super states to identify which types of fingerprint then it can match the given fingerprint image with the image which are kept in database.

HMM IN PATTERN RECOGNITION

HMM are statistical models that consist of several states. At each step a transition to another state depending on a transition probability matrix is performed and a symbol is created depending on a probability density function (pdf) that is assigned to each state.

A single HMM is trained for each person in the training set using the Baum-Welch algorithm. The viterbi algorithm is used to determine the probability of each fingerprint pattern. HMM are statistical models that consist of several states. At each step a transition to another state depending on a transition probability matrix is performed and a symbol is created depending on a probability density function (pdf) that is assigned to each state.

A higher level HMM Models the sequence of columns in the image. Instead of a probability density function the states of the higher level model (super states) have a one-dimensional HMM to model the cells inside the columns.

The probability density functions of the lower level models are omitted The Baum-Welch algorithm determines the parameters corresponding to a local maximum of the likelihood function depending on the parameters of the initial model. Therefore, it is crucial to use a good initial model for the training. Researchers train a general initial model on all fingerprints in the training set using the Baum-Welch algorithm. This common model is refined on the training fingerprints of one person to obtain the model for this person.

Hidden Markov Models are employed in a wide variety of fields including speech recognition, econometrics, computer vision, signal processing, cryptanalysis and computational biology. In speech recognition, hidden Markov Models can be used to distinguish one word from another based upon the time series of certain qualities of a sound.

FINGERPRINT RECOGNITION SYSTEM (FRS)

The Fingerprint Recognition System (FRS) uses following four steps to recognize the given fingerprint image (Fig. 3):

- Preprocessing
- Feature extraction
- HMM training
- Fingerprint Matching

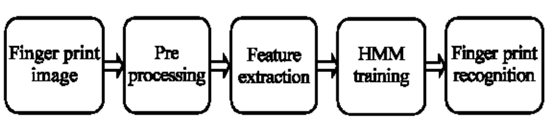

Fig. 3: Fingerprint Recognition System using HMM

The preprocessing involves some processes such as remove background, reduces noise exist on image, enhance the definition of ridges against valleys and produces the clear thinned minutia (Mary Lourde and Khosla, 2010). A fingerprint image may be one of the noisiest of image types. This is due to the fact that finger tips become dirty, cut, scarred, creased, dry, wet and worn, etc. The image enhancement step is designed to reduce this noise and to enhance the clear definition of ridges against valleys. Two image processing operations designed for these purposes are the adaptive matched filter and adaptive thresholding. Even though there may be discontinuities in particular ridges, one can always look at a local area of ridges and determine their flow. This filter is applied to every pixel in the image. Based on the local orientation of the ridges around each pixel, the matched filter is applied to enhance ridges oriented in the same direction as those in the same locality and decrease anything oriented differently. The incorrect ridges can be eliminated by use of the matched filter (Maltoni *et al*., 2003).

From the enhanced minutia, minutia points (features) are extracted using feature extraction techniques (Gu *et al*., 2006). The fingerprint minutiae are found at the feature extraction stage. Operating upon the thinned image, the minutiae are straightforward to detect. Endings are found at termination points of thin lines. Bifurcations are found at the junctions of three lines. There will always be extraneous minutiae found due to a noisy original image or due to artifacts introduced during matched filtering and thinning. These extraneous features are reduced by using empirically determined thresholds (Kant and Nath, 2009). For instance, a bifurcation having a branch that is much shorter than an empirically determined threshold length is eliminated. Two endings on a very short isolated line are eliminated because this line is likely due to noise. Two endings that are closely opposing are eliminated because these are likely to be on the same ridge that has been broken due to a scar or noise or a dry finger condition that results in discontinuous ridges. Endings at the boundary of the fingerprint are eliminated because they are not true endings but rather the extent of the fingerprint in contact with the capture device. Feature attributes are determined for each valid minutia found (Gu *et al*., 2006).

The extracted feature of fingerprint is accepted by the pseudo 2D HMM to classify fingerprint image separately according to the pattern type such as right loop, left loop, whorl and arch.

THE PSEUDO 2D HMM FOR FINGERPRINT RECOGNITION

A HMM provides a statistic model for a set of observation data sequences (Senior, 1997). It includes two forms of stochastic finite process. One is a Markov chain of finite state which describes the transfer from one state to another the other describes the probabilities between states and observation data.

A HMM is a state transition probability matrix, an initial state probability distribution and a set of probability density functions associated with the observations for each state. Typically a HMM is a 1D structure suitable for analyzing 1D random signals for example speech signals. A 1D HMM can be developed to a pseudo 2D structure (Fig. 4) by extending each state in a 1D HMM as a sub HMM. By this way the HMM consists of a set of super states, along with a set of pseudo states. The super states were used to model 2D data along one direction with the pseudo HMM modeling the data along the other direction.

In this study, the pseudo HMM scheme of an input Fingerprint image is shown as in Fig. 5. The pseudo HMM includes four super states each super state represents the different patterns of finger print image such as right loop, left loop, whorl and arch. Each super state is composed of three sub states (pseudo states) horizontally.

A fingerprint image is scanned with a W×H sampling window (image block) left to right and top to bottom. The overlap between adjacent windows is N pixels distance in the vertical direction and M pixels distance in the horizontal direction. In this way, a fingerprint can be divided into a Y×X image blocks matrix and the size of each block is W×H. This technique can improve the ability of a pseudo HMM to model the neighborhood relations between the sampling windows.

Each W×H image block includes four sub image blocks. By estimating the local orientation of each sub

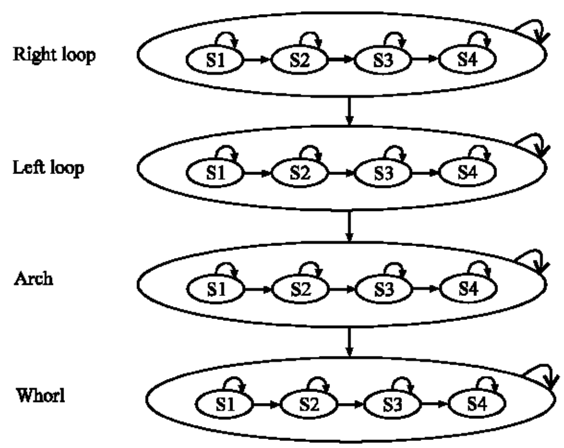

Fig. 4: The pseudo 2D HMM structure

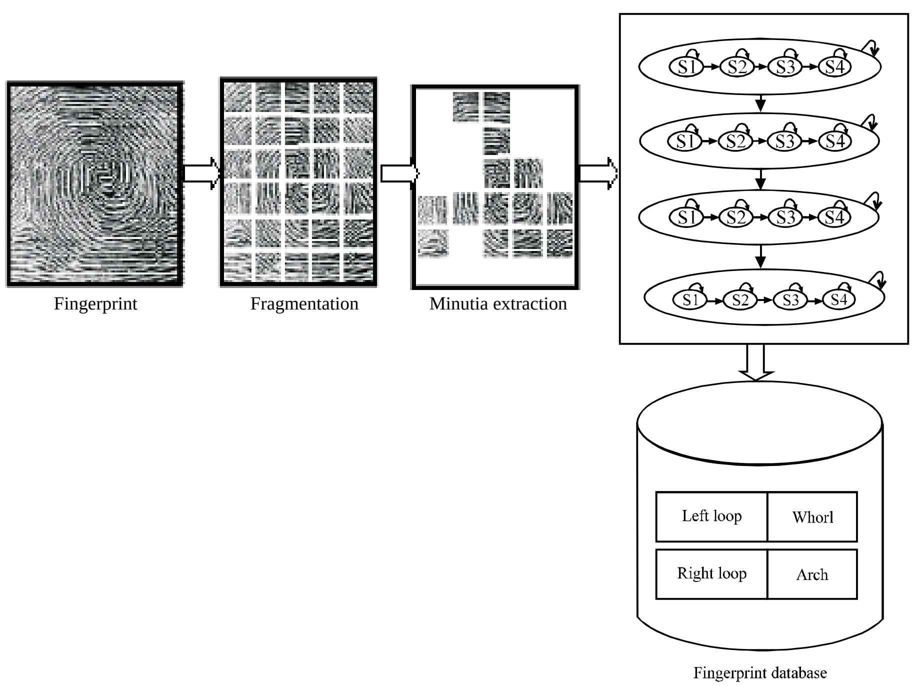

Fig. 5: Pseudo 2D HMM training

block, researchers can get an observation vector which can described the features of the W×H image block reasonably. Each W×H image block can be represented with an observation vector and a fingerprint image can be divided into a Y×X image blocks matrix, so a fingerprint can be described with an 4×Y×X observation vector sequence.

Since, a captured fingerprint appears randomly in an image, a preprocessing is needed for adjusting the location of a fingerprint and setting the reference area which includes the whole area for fingerprint feature extraction.

A reference point of a fingerprint is detected and the location of the reference point is adjusted to the image center. The reference point detection algorithm based on the orientation field of fingerprint images has been described in reference (Choi *et al*., 2011). The fingerprint is rotated based on the ridges structure around the reference point (Girgisa *et al*., 2007). After the location of a fingerprint is adjusted, a reference area can be set.

THE VITERBI ALGORITHM FOR FINGERPRINT RECOGNITION

Suppose researchers are given a Hidden Markov Model (HMM) with state space S, initial probabilities $\pi_{i,j}$ of being in state i and transition probabilities $a_{i,j}$ of transitioning from state i to state j. Say researchers observe outputs $y_1,..., y_T$. The most likely state sequence $x_1,..., x_T$ that produces the observations is given by the recurrence relations:

$$V_{1,k} = P(y1|\,k).\pi_k$$
$$V_{t,k} = P(y_t\,|\,k).\max_{x\in S}(a_{x,k}.V_{t-1,x})$$

Here, $V_{t,k}$ is the probability of the most probable state sequence responsible for the first t observations that has k as its final state. The Viterbi path can be retrieved by saving back pointers that remember which state x was used in the second equation.

Let Ptr(k, t) be the function that returns the value of x used to compute $V_{t,k}$ if t > 1 or k if t = 1. Then:

$$x_T = \arg\max_{x\in S}(V_{T,x})$$
$$x_{t-1} = Ptr(x_t, t)$$

The complexity of this algorithm is O (T x | S|^2).

Algorithm 1 (Viterbi algorithm for fingerprint recognition):

Input: The observation space $O = \{o_1, o_2,..., o_N\}$, the state space $S = \{s_1, s_2,..., s_K\}$ Sequence of observations $Y = \{y_1, y_2..., y_T\}$ such that $y_t == i$. If the observation at time t is o_i, transition matrix A of size K.K such that A_{ij} stores the transition probability of transiting from state s_i to state s_j, mission matrix B of size K.N such that B_{ij} stores the probability of observing o_j from state s_i, an array of initial probabilities π of size K such that π_i stores the probability that $x_1 = s_i$.

Output: The most likely hidden state $X = \{x_1, x_2,..., x_T\}$ sequence.

```
function VITERBI (O, S, π, Y, A, B): X
   for each state s_i do
      T_1[i, 1]←π_i B_iy_1
      T_1[i, 1]←0
    end for
  for I←2, 3, ..., T do
     for each state s_j do
T_1[j,i]←max (T_1[k,i-1].A_kj.B_jyi)
         k
T_2[j,i] ← arg max (T_1[k,i-1].A_kj.B_jyi)
               k
            end for
     end for
   z_T←arg max (T_1[k,T])
            k
   x_T←s_zT
      for i←T,T-1,...,2 do
         z_i-1←T_2[z_i,i]
         x_i-1←s_zi-1
      end for
    return X
end function
```

For recognition, a two-dimensional Viterbi algorithm will employ to search for the best combination of states with maximum a posteriori probability and map each block to a fingerprint pattern. This process is equivalent to search for the state of each block using an extension of the variable-state Viterbi algorithm presented in algorithm 1 based on the new structure in Fig. 4. To reduce the computational complexity, researchers only use N sequences of states with highest likelihoods out of the possible states. A generalization of the Viterbi algorithm, termed the max-sum algorithm (or max-product algorithm) can be used to find the most likely assignment of all or some subset of latent variables in a large number of graphical models, e.g., Bayesian networks, Markov random fields and conditional random fields. The latent variables need in general to be connected in a way somewhat similar to an HMM with a limited number of connections between variables and some type of linear structure among the variables. The iterative Viterbi decoding can find the subsequence of an observation that matches best (on average) to a given HMM. Iterative Viterbi decoding research iteratively by invoking a modified Viterbi algorithm and reestimating the maximum likelihood probability score for filler until convergence. An alternative algorithm the Lazy Viterbi algorithm has been proposed recently (Gu *et al*., 2006). For many codes of practical interest, under reasonable noise conditions, the lazy decoder (using Lazy Viterbi algorithm) is much faster than the original Viterbi decoder (using Viterbi algorithm) (Senior, 1997). This algorithm works by not expanding any nodes until it really needs to and usually manages to get away with doing a lot less work (in software) than the ordinary Viterbi algorithm for the same result however, it is not so easy to parallelize in hardware. Moreover, the Viterbi algorithm has been extended to operate with a deterministic finite automaton in order to improve speed for use in stochastic letter to phoneme conversion.

The pseudo HMM is built by selecting different samples of the same fingerprints and implementing a training processing which is a process for estimating the corresponding pseudo HMM parameters. Fingerprint matching processing of a test fingerprint is to find the maximum matching likelihood of the pseudo HMM among different fingerprints by using Viterbi algorithm.

PERFORMANCE ANALYSIS

The combination of those classifiers in real time systems becomes difficult to implement in existing fingerprint authentication system using hybrid classifier.

Even when the Viterbi algorithm is not actually implemented in this system, calculation of its performance shows how far the performance of less complex schemes is from ideal and often suggests simple suboptimum schemes that attain nearly optimal performance. Viterbi algorithm works fast when compared to other algorithm such as forward backward algorithm and maximum expectation algorithm.

Since, each pattern is considered as a separate super states and separate database is maintained for each super state, there is no need to search entire database while recognizing particular pattern of fingerprint.

The Pseudo 2D HMM can achieve improved recognition rate by using the Viterbi algorithm. The Viterbi algorithm is a recursive optimal solution to the problem of estimating the state sequence of a finite-state Markov process observed.

CONCLUSION

The fingerprint recognition based on the pseudo 2D HMM approach only depends on the orientation field of a fingerprint, so it is less sensitive to the noise and distortions of a fingerprint image than the conventional approaches in which the dependent parameters include more fingerprint details. The algorithm skipped the processes of thinning the ridge image and selecting minutiae.

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