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Accelerated Q-learning approach for minutiae extraction in fingerprint image

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***Abstract*- Fingerprint recognition is a physiological biometric technique. It is most dependable as compare to other biometric technique. Fingerprint recognition involves preprocessing, minutiae extraction and post processing stages. In conventional approaches preprocessing stage include image processing steps to reduce noise. Image processing steps are extremely sensible against noise. A Q-learning approach used for minutiae extraction generates insensitiveness against noise but it also gives success for wrong ridge path which expend processing time. In this paper we have proposed accelerated Q-learning approach for minutiae extraction which calculate Q-value for both success and fail state. In proposed method we follows ridges if it gets fail state it leaves that ridge path otherwise it will continue to follow that ridge and calculate Q-value for success state. Proposed method reduces processing time and also improves efficiency against noise.**

***Keyword*- fingerprint images, minutiae extraction, ridge endings, ridge bifurcation, fingerprints recognition.**

I. INTRODUCTION

Humans recognize each other through behavioral and physiological characteristics such as a fingerprint or a voice sample. The characteristics are measurable and unique. To achieve trustworthy recognition we use something that really characterizes the given person. Biometrics offer automated methods of recognition.

Fingerprint recognition is the oldest technique which is commonly using in biometric system for different security purpose. Fingerprints contain a large amount of data. Because of the high level of data present in the image, it is possible to eliminate false matches and reduce the number of possible matches to a small fraction. This means that the fingerprint technology can be used for identification even within large databases [1].

Fingerprint has useful information in the form of line structure. This line structure has black and white lines. Black line is known as ridges which is having high gray scale values and white lines is known as valleys which is having low grayscale values. Fingerprint information has been classified by different features which are known as minutiae. Most automatic systems for fingerprint comparison are based on minutiae matching Minutiae are local discontinuities in the fingerprint pattern [2]. A total of 150 different minutiae types have been identified. In practice only ridge ending and ridge bifurcation minutiae types are used in fingerprint recognition. Examples of minutiae are given in (Figure 1) [3] [4].

Figure 1 Minutiae in the fingerprint image

In this paper we have proposed an accelerated q-learning based method in which we follow ridges and calculate q value. We stop following the ridges only when we get Q_F. In last this calculated value is treated as minutiae. Conventional approaches [5] for minutiae extraction used image processing steps. As we know image processing steps are highly sensitive with the noise. This can we removed by agent based approach. Asker M. Bazen and Martijn van Otterlo, 2001, [6] have proposed an agent based approach learnt based on SARSA learning technique in which an autonomous agent walks around on the fingerprint images and learns how to follow ridges in the fingerprint and how to recognize minutiae further. One Problem with SARSA approach is that it requires exploring the policy which increases the convergence speed. Sandeep Tiwari and Neha Sharma 2012, [3] have proposed a Q-learning approach which is insensitive to the policy of exploration. Agent learns by observing the relation between neighborhood grayscale values of ridges and find original minutiae. The proposed approach significantly reduces convergence speed due to insensitiveness to the policy exploration.

II. ACCELERATED Q-LEARNING

Accelerated q-learning algorithm is proposed for environment having both goal and fail states. It extends q-learning, a well-known scheme in reinforcement learning [7]. Reinforcement learning (RL) is one of machine learning methods, which includes the temporal difference algorithm proposed by Sutton [8] and the Q-learning proposed by Watkins [9].

In the RL, there is an interaction between agent and environment where the agent has to go through numerous trials in order to find out the optimal greedy action.

In Q-learning, agent has the ability to learn state-action value using selected actions in the state without the model of environment. Updating equation of the Q value is as follows:

$$Q(s,a) \leftarrow Q(s,a) + \alpha(r + \gamma \max(Q(s',a') - Q(s,a) \quad \ldots\ldots\ldots [1]$$

Where α is the learning rate and γ is the discount rate. As γ gets closer to 0, the agent will tend to consider only immediate reward, whereas the agent will consider future reward with greater weight as γ becomes closer to 1.

Unlike this conventional Q-learning, the Accelerated Q-learning algorithm keeps track of the past failure experiences as a separate fail state-action value, Q_F. Agent uses this value along with a goal state-action value, Q_N, which is calculated and updated using conventional Q-learning, to modify the exploratory behavior during learning phase.

A failure experience of agent is a situation when the agent enters into a fail state. In this case, environment has fail states in its state and action space. In Q-learning, the agent receives a punishment, i.e. a negative reward, from the environment when it reaches fail state. By receiving the negative reward, the Q value of the state-action pair reaching the fail state is decreased.

There are two separate state and action spaces to consider both conventional Q-learning and failure experience of the agent. Normal Q value, Q_N, is defined as state-action value of the conventional Q-learning where Q_N is updated by using (1). Fail Q value, Q_F, is defined as state-action value based on the failure experience of the agent. Fig. 1 shows the block diagram of Accelerated Q-Learning algorithm [10].

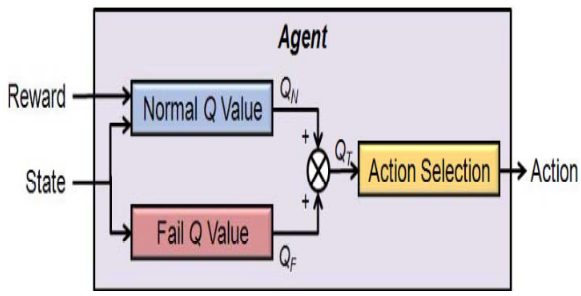


Fig. 2. Block diagram of accelerated Q-learning having fail states

Fail Q value based on the failure experience of the agent is calculated as follows:

$$e^{QF/\tau} = 1 - pF\,,$$

$$QF = \tau \ln(1 - pF) \ldots\ldots\ldots [2]$$

Where τ is a temperature to control the trade-off between exploration and exploitation, and p_F is a failure probability, which is obtained by the failure experience of the agent and applied to the state-action pairs, Q_F. Since failure probability has a value between 0 and 1, Q_F is always a negative value in (2).

III. Accelerated Qlearning For Minutiae Extraction

First we load a fingerprint image and apply Gaussian noise. Now apply thinning on image up to one pixel value. Thinning process made calculation very easy and also reduced some noise .Than calculate L (Termination and Bifurcation points) by monitoring neighborhood values. Initialize reward as L. State Q has selected randomly from ridges. Apply accelerated Q-Learning by following the ridges .It only stops following the ridge if it calculates QF otherwise it follows that ridge up to last value and calculate Q. In last elected maximum Q-value as minutiae.

A. *Proposed Algorithm*

1. $Load\ fingerprint\ image$
2. $Apply\ noises\ on\ images$
3. $Apply\ Thinning\ on\ noisy\ image$
4. $Calculate\ neighborhood\ values\ L$
5. $If\ (L = 1)$
6. $Than\ calculate\ termination\ point$
7. $If\ (L = 2)$
8. $Than\ calculate\ bifurcation\ point$
9. $Initialize\ R = L$
10. $Set\ state\ Q\ randomly$
11. $Apply\ accelerated\ Q - learning$
12. $If\ \ find\ QF$
13. $Stop$
14. $Otherwise$
15. $Calculate$ $Q(s,a) \leftarrow Q(s,a) + \alpha(r + \gamma \max(Q(s',a') - Q(s,a))$
16. $Minutiae = maximum(Q)$

B. *Result Analysis*

Accelerated Q-Learning on original image:

In this section we have analyzed the step wised results on fingerprint image with and without noise. First we processed the image using thinning up to one pixel value. This step made the computation very simple. Than we compute bifurcation and termination points using 3×3 mask. This step could have some spurious points. So, we required to apply Accelerated Q-Learning. First we set all the parameters, Learning rate α=0.1 and γ=0.9.Than Set Reward as bifurcation and termination values. Select some random point on a ridge and follow that ridge up to end point. At Each point of ridge we calculate Q-value and decide either it is a fail state or success state. If it is a fail sate we stop following that ridge and switch to another. Otherwise compute Q-value using conventional Q-Learning method. In last we selected maximum Q-value as minutiae. Fig. 3 shows the results on image without noise and learning graph. Constant Line in Learning time graph represented that agent has learnt.

Original image

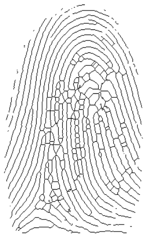
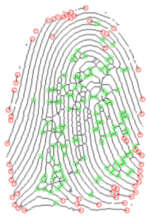
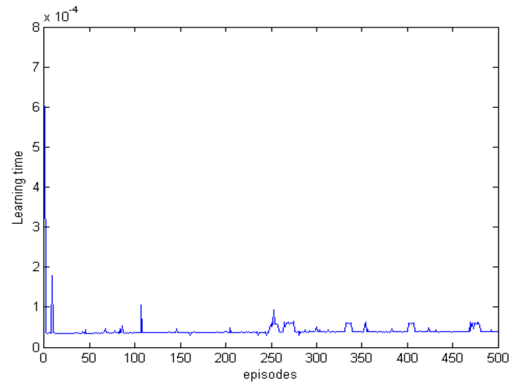


Image after thinning

Before Accelerated - Q-Learning



Final minutiae



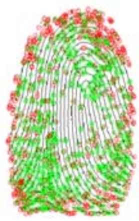
Learning Graph

Fig.3

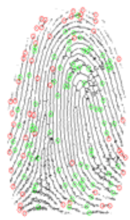
Accelerated Q-Learning on image using Gaussian noise:

Image with noise

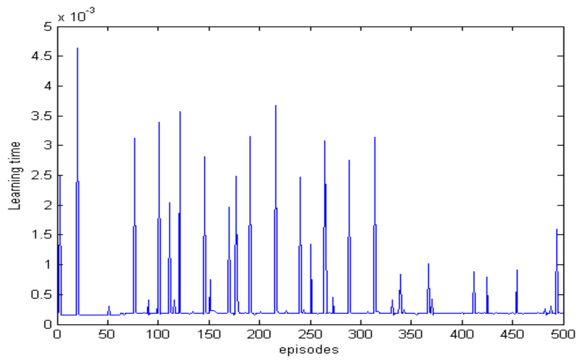
Image after thinning



Before Accelerated Q-Learning



Final minutiae



Learning Graph

Fig.4

In fig. 4 we have represented the results with noise. From the comparative analysis of processing time presented in table 1 we can say that the proposed method can also provide good result with noise but required more episodes to learn the agent.

Table 1

Method's	Processing Time(s)
Ratha et al.'s method	1.8 sec.
Ariel Unanue and AdrianaZapico's Method	0.3 sec.
Asker M. Bazen and Sabih H. Gerez's Method	Not provided
Sandeep et al.'s Method	0.158 sec
Our method	0.08 sec

IV. RESULT

In this paper we have proposed accelerated Q-Learning for minutiae extraction from fingerprint image which is more efficient than other conventional approaches in prospect of processing time. We can simply recognize minutiae against noisy image. We have computed processing time 0.08 sec against noisy image. Proposed method is implemented with the Gaussian noise, so, implementation with other noises is remaining as future work.

REFERENCE

[1] Anil K. Jain, Arun Ross and Salil Prabhakar, "An Introduction to Biometric Recognition "Appeared in IEEE Transactions on Circuits and Systems for Video Technology, Special Issue on Image- and Video-Based Biometrics, Vol. 14, No. 1, January 2004.

[2] Salil Prabhakar, Anil K. Jain and Sharath Pankanti,"Learning Fingerprint minutiae location and type. Pattern "Recognition Society. Published by Elsevier Science Ltd, 2003.

[3] Sandeep Tiwari and Neha Sharma," Q-Learning Approach for minutiae extraction from fingerprint image" Procedia Tecnology.Elsevier 2012.

[4] D. Maio and D. Maltoni,"Direct gray-scale minutiae detection in fingerprints" IEEE Trans. PAMI, 19(1):27–39, January 1997.

[5] Asker M. Bazen and Sabih H. Gerez," Segmentation of Fingerprint Images" Workshop on Circuits, Systems and Signal Processing, Veldhoven, the Netherlands, November 2001.

[6] Asker M. Bazen and Sabih H. Gerez , Martijn van Otterlo and Mannes Poel" A Reinforcement Learning Agent for Minutiae Extraction from fingerprint"13th Belgian-Dutch Conference on Artificial Intelligence October 25-26, 2001, Amsterdam, The Netherlands

[7] Leslie Pack Kaelbing, Michael L.Littman and Andrew W. Moore"Reinforcement Learning: A Survey"AI Access Foundation and Morgan Kaufmann publisher, 1996

[8] R.S. Sutton, D. Precup and S. Singh,"Between MDPs and Semi-MDPs: A Framework for Temporal Abstraction in Reinforcement Learning,"Artificial Intelligence, vol. 112, pp. 181-211, 1999.

[9] C.J.C.H. Watkins and P. Dayan, "Q-learning," Machine Learning, vol. 8,pp. 279-292, 1992.

[10] In Wonpark and Jong-Hwan Kim" and "Kui-Hong Park,"Accelerated Q-Learning for Fail State and Action Space ", 2008 IEEE International Conference on Systems, Man and Cybernetics (SMC 2008).