

## Chapter 6

# Markov Chain for Multimodal Biometric Rank Fusion

### ABSTRACT

*Markov chain is a mathematical model used to represent a stochastic process. In this chapter, Markov chain-based rank level fusion method for multimodal biometric authentication system is discussed. Due to some inherent problems associated with existing biometric rank fusion methods, Markov chain-based biometric rank fusion has recently emerged in biometric context. The notion of Markov chain and its construction mechanisms are presented along with discussion on some early research conducted on Markov chain in other rank aggregation frameworks. This chapter also presents a detailed description of recent experimentations conducted to evaluate the performance of Markov chain-based biometric rank fusion method in a face, ear, and iris-based application framework.*

### 1. INTRODUCTION

In the previous chapter, different methodologies for rank level fusion were presented. These methods included plurality voting method, highest rank method, Borda count method, logistic regression method and quality based rank fusion method for multimodal biometric system. Among those methods, the logistic regression method consistently provides high Performance, however it still has

some drawbacks. The results obtained through this method can be varied significantly for different datasets due to their diverse qualities. Logistic regression method for a multimodal dataset with the same image quality will produce results similar to Borda count method, as the assigned weights to different biometric matchers' outputs will be the same. Thus, allocating appropriate weights to different matchers (comparing different quality datasets) requires appropriate learning technique,

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which is time consuming. Also, inappropriate weight allocation can result in wrong recognition results. Further, the size of the multimodal biometric database is usually large and thus only the top few results are considered for the final reordered ranking. Hence, a very common scenario of a rank based multimodal biometric system is that some results may rank at top by a few classifiers and the rest of the classifiers do not even output the result. In this situation, the logistic regression approach cannot produce a good recognition performance. Thus, a novel rank fusion method utilizing Markov chain has been recently developed at BT Lab at the University of Calgary. This method can be efficiently used in multimodal biometric authentication system comprised of varied quality datasets. The method has been successfully used in other information fusion applications. In this chapter, an overall description of this method is given. It includes Markov chain definition, advantages and disadvantages of Markov chain in multimodal biometric fusion scenario, previous research on Markov chain and its application in rank level fusion.

## 2. MARKOV CHAIN

A Markov chain is named for the Russian mathematician Andrei Andreyevich Markov. It is a mathematical model that can be thought of a being in exactly one of a number of states at any time (Markov, 1906). A Markov chain has a set of *states*,  $S = \{s_1, s_2, \dots, s_r\}$ . The process starts in one of these states and moves successively from one state to another (Kemeny, Snell, & Thompson, 1974). Each move is referred to as a *step*. If the chain is currently in state  $s_i$ , then it can move to state  $s_j$  with a probability  $p_{ij}$ . This probability is preset at the beginning of the process and does not depend on how the state was reached. The probability  $p_{ij}$  is referred to as *transition prob-*

*abilities*. The process can remain in the same state with probability  $p_{ii}$ . The starting state is given by an initial probability distribution (Kemeny, Snell, & Thompson, 1974).

The following example illustrates how Markov chain operates. Assume that there is a sports team which performance highly depends on its previous history of winning or losing. If the team wins, then there is 50% chance it will win the next game, and 25% chance it will tie or lose the next game. If the team ties, there is 75% it will tie again, and 25% it will lose. Finally, if the team loses, there is 50% chance it will lose next game and 50% chance it will win.

Now we can build a Markov chain. States in this example are W (Win), T(Tie) and L(Lose). Transitional probabilities can be represented in a matrix:

$$P = \begin{matrix} & \begin{matrix} W & T & L \end{matrix} \\ \begin{matrix} W \\ T \\ L \end{matrix} & \begin{pmatrix} 1/2 & 1/4 & 1/4 \\ 0 & 3/4 & 1/4 \\ 1/2 & 0 & 1/2 \end{pmatrix} \end{matrix} \quad (6.1)$$

The entries in the first row of the matrix **P** in this example represent the probabilities for the win, tie or lose of the team during the next game. The entries in the second and the third row represent probabilities of win, lose or tie following the tie (second row) or the loss (third row) Such an array is commonly called the *matrix of transition probabilities*, or the *transition matrix*.

The matrix allows to determine, given the state  $i$ , the probability of win, loss or tie in one, two, or any number of consequent games in the future.

Let us consider one more detailed example. It showcases the main principle of a Markov chain. Suppose, a library book is shared by two friends, Mike and Charles. If the book is borrowed by Mike during a week, there is an 80% chance that he will keep the book for the next week. On the

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