A Bio-Inspired Music Genre Classification Framework using Modified AIS-Based Classifier

Noor Azilah Draman, Sabrina Ahmad, Azah Kamilah Muda
Faculty of Information and Communication Technology
University of Technical Malaysia Melaka (UteM)
{azilah, sabrinaahmad, azah}@utem.edu.my

ABSTRACT

For decades now, scientific community are involved in various works to automate the human process of recognizing different types of music using different elements for example different instruments used. These efforts would imitate the human method of recognizing the music by considering every essential component of the songs from artist voice, melody of the music through to the type of instruments used. Various approaches or mechanisms are introduced and developed to automate the classification process since then. The results of these studies so far have been remarkable yet can still be improved. The aim of this research is to investigate Artificial Immune System (AIS) domain by focusing on the modified AIS-based classifier to solve this problem where the focuses are the censoring and monitoring modules. In this highlight, stages of music recognition are emphasized where feature extraction, feature selection, and feature classification processes are explained. Comparison of performances between proposed classifier and WEKA application is discussed. Almost 20 to 30 percent of classification accuracies are increased in this study.

KEYWORDS

Artificial Immune System, Modified AIS-based Classifier, Censoring and Monitoring Modules, Classification, Song Genre.

1 INTRODUCTION

Audio signals in songs contain a great deal of information that can be used to index and classify music data has led to the consideration of audio classification studies as an important and challenging research area [1]. An efficient mechanism of representing audio data should be used to represent low-level sound properties for describing, recognizing and identifying different music sounds. According to [2], the extracted features used in the classification process need to be comprehensive in which it can represent music data very well; compact where they require small storage space; and efficient in the sense that it can be computed efficiently.

Apart from using the appropriate music contents, we also need to use good classifier to classify various categories of music. Previous music related studies are to introduce new music features to represent certain aspect of music which often related to introducing new extraction technique to obtain the music features [3], [4] or to manipulate fusion of music features to classify music genre [5].

This research is about investigating the music signals to search for patterns or features that can be used to recognize and classify music genres. The research is also investigating an algorithm in the AIS domain which focuses on the negative selection algorithm, and proposes a modified version of the algorithm. There are studies that focused and investigated an approach in the AIS domain called the clonal selection algorithm previously [6][7] but, not the negative selection algorithm (NSA). NSA is applied in this music genre classification study because it has been repeatedly used in pattern recognition studies and produced high quality results. The ability to recognize different patterns using censoring and monitoring modules are also inspired us to investigate the technique and find the solution to the music genre classification problems.

2 BACKGROUND OF RESEARCH

In music-related studies, research is initiated to solve problems that occur during recognition such as, deciding which song belongs to which genre. [10], for example, did the early work of classifying songs into different categories of genre using human auditory skills. Finding solutions to increase the performance of the automation process in the classification study is another problem often investigated in the music analysis area. Various attempts to solve this problem have been reported in [8] – [16]. Not only the problem of automating the process of classification but the question of how to fill the gap of accuracy behind human skilled classification also need to be answered and solved. [3] introduced a new technique to extract the music features called Daubechies Wavelet Coefficient Histograms (DWCHs to overcome the problem of classification accuracies in the previous study. The authors used the Daubechies wavelet filter, *Db8*, to decompose music signals into layers where at the end of each layer they constructed histograms of coefficient wavelet. During experiments they combined the new feature with features [3] and improved the classification accuracies but not by much.

There is also another attempt that emphasizes on using the pitch, rhythm, and timbre contents to classify music into different genres [17]. [18] proposed a solution to the problem where the authors introduced a new feature extraction method called *InMAF*. [15] attempted to classify the music genre using MIDI (Musical Instrument Digital Interface) and audio features like the pitch, rhythm and timbre features by using the data from [19] study which contained two different sets of contents, the first are MIDI features and the other group are the audio features.

A recent study proposed a new approach to classify music genre by emphasizing on the features from cepstral contents: MFCCs, OSC and MPEG 7 representations [20], where they introduced a novel set features derived from modulation spectral analysis of the spectral representations. [21] developed an AIS-based clustering and classification algorithm which emphasized the ability of the algorithm to adapt and cope efficiently in the complex and changing environments of the immune system. The vital feature of this algorithm compared to other classifiers is their ability to discriminate the self or non-self cells, especially in the situation where the size of non-self cells is larger than self-cells. Later in 2008, they proposed a novel AIS-based classification approach to classify music genres.

[6] proposed a new version of the artificial immune recognition system (AIRS) which was initially developed as a new classification technique based on the humans' immune system [22]. The previous problem of classifying multiple classes at one time has been resolved in this study as ten music genres were classified and produced a better performance with a high accuracy (88 percent). The new version of AIRS has highlighted the nonlinear coefficient of the clonal rate, which has assigned more resources to the detectors with a higher affinity level and has allocated less resource to the detectors with a lower affinity level, which was essential to the recognition processes. The features selection technique applied in the study also contributed to better performances in the music genre classification studies.

[7] described similar experiments to those discussed earlier, where the new version of AIRS classifier has changed the linear method to a nonlinear method of allocating the resources to the clonal rate. Not only the classifier classify more than two types of cells at one time, the classification performances also produced better performances and provided better accuracies than the previous studies.

3 AIS-BASED MUSIC GENRE CLASSIFICATION FRAMEWORK

The artificial immune system (AIS) is defined as mechanisms that manipulate, classify and represent data, and intelligent methodologies that follow a biological paradigm which is the human immune system. It is also an adaptive system that follows the immune theories and functions, principles and method to solve real world problem [23][24]. The definition not only stresses the immune system approach to solve problems, but it also includes mathematical functions that define all the mechanisms of the immune system to be applied to tasks in various fields ranging from optimization, pattern recognition, machine learning, data mining, computer security to fault diagnosis [24]. According to [25], there are at least eleven key elements in the immune system that provide important aspects for the field of information processing: recognizing, extracting features, variety, learning, remembrance, scattered detection, self-regulation, threshold mechanisms, co-stimulation, dynamic protection and probabilistic detection.

AIS are adaptive systems, emulating human body immunology system to solve problems. It is concerned with abstracting the whole concept of immune system to computational systems in solving problems from mathematics, engineering and information technology point of view. AIS, is created based upon a set of general purpose algorithms that are modelled to generate artificial components of the human immune system [26]. AIS, is defined as an adaptive system which is enthused by biological immunology and observed functions, principles and models to problem solving.

Negative selection algorithm is introduced in [27] where the idea was inspired by negative selection of T-cells in thymus. The algorithm focused on recognizing self or non-self cells where it will eliminate the T-cells that are not recognized by the thymus. Detail explanations of how negative selection algorithm works can be found in [28]. As has been investigated before, it would be impossible to apply NSA without modification in each study as each problem and solutions were also different. However, we will not discuss the NSA and how it changes in each study as it is not in this research scope. To be able to apply the AIS approach in solving the music genre recognition problem, we need to follow and understand the basic things that are needed based on the basic elements of AIS framework [23] [29]:

1) a representation for the components of the system
2) a set of mechanisms to evaluate the interaction of elements with the environment and with each other
3) procedures of adaptation that govern the dynamic of the system

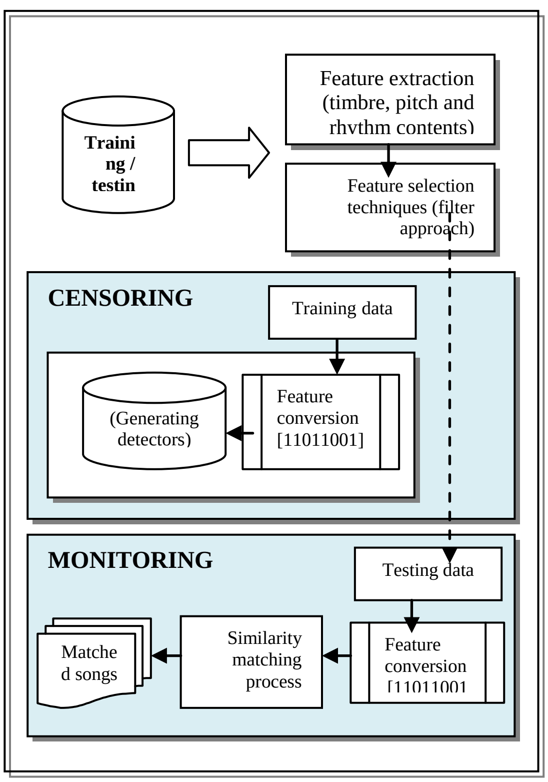

Figure 1. AIS-based music genre classification framework

Figure 1 illustrates the structure of our proposed AIS-based music genre classification framework. First we extract the music features from the songs then we transform them into binary bit strings. Two highlighted processes, the censoring and monitoring modules depict two important parts of AIS-based model in recognizing different patterns. The following sections discuss each step in the recognition stage, that are the feature extraction, feature selection and feature classification which comprises two important processes; censoring and monitoring.

3.1 Music Features Extraction

The feature extraction in the content-based definition is a process of calculating the music contents to provide numerical representations to characterize the music [3]. In order to get quality feature representations and quality results in the music recognition work, the choice of selected features should be able to reflect the underlying information about the music. For example, if there are different genres of music that need to be identified, the extracted music features should be able to represent all types of those genres.
According to [30], the extracted features from music data should be able to fulfil two criteria. The first criterion is related to the feature space where objects that are considered similar will be located next to each other and the differences between object regions can be clearly seen on that feature space. The second criterion is the extracted technique used should be able to conserve all-important information contained in the data. The

human perception of the sounds is the way listeners generate music label during the identification process and it happens whenever they hear the sounds. Technically, the humans also depend on the features extracted from the sounds they hear in order to recognize the sounds. The auditory system in human being is a very sophisticated system where it can automatically separate the sounds and immediately identify the source.

[30] stated that there are two categories of extracted features used in music signal analysis: 1) perceptual features and 2) physical features. The perceptual features were based on the perception of sounds when humans hear them, for example the high or low pitch, the melody and the frequency. The physical features on the other hand were produced in mathematical computing mechanisms during the sounds analysis using signal-processing concepts. The perceptual and physical features were related to each other.

The physical features were labelled as physical because the extraction process imitated the perceptual features that human processed, for example, a slow song that contains harmony sounds is assumed as a Ballard song because the physical features used to recognize it were calculated from the song's slow beat using mathematical functions.

Three music contents were introduced in [3], which are the pitch, timbre, and rhythm. Further elaboration on the music contents are as followed:-

Timbre. In music, timbre is defined as the quality of sounds or the colours of music and is produced when a musical instrument played music notes that contained more than one level of frequencies. It allows a person to distinguish different instruments playing the same pitch and loudness. The human ear and brain have magnificent capabilities that can detect even a very small variation of timbre quality in the music.

These capabilities were the reason why humans can discriminate two different instruments playing similar notes, similar pitch, or loudness.

The major aims of the timbre perception studies are to develop a theory of sounds classification [32]. In the study, the author focused on experimenting different sounds coming from various orchestra instruments. The sounds contained similar pitch, loudness, and duration. The study aimed to get perceptual relationships between the instruments and it showed that timbre could discriminate different sources of sounds in a note. According to [34], timbre content is the common music feature that is used to distinguish different aspects of the music and instrumentations, and if they are combined with other features such as rhythm and tonal characteristics, they usually are enough to discriminate various styles of the music.

Rhythm. Rhythm, by musical definition, is the musical time. It relates to the beat of music. Beat represents the music notes that can be in a whole, a half or a quarter long. One whole note represents a length of four beats. Rhythm is the flow of music. It organizes the notes within the music pace and tempo is the term used to indicate the arrangement of the music pace. Tempo and rhythm is normally used together to describe a slow or a fast song.

In music research, many studies have focused on the rhythm content that emphasized the tempo and beat of the music to recognize the songs. Rhythm can be represented by various terms in music analysis, ranging from low level audio signal features to a more abstract or symbolic concept [33].

Theoretically, the rhythm represents the beat, and the beat is the note of the music. Note in general, represents certain patterns of a song and these patterns technically can be used to recognize the music. The music pattern is the symbolic information that represents various types of music for example, songs from different regions or ethnic groups that generally tell stories about their way of life or anything related to their community through their songs.

There are studies that focused on analysing repeating patterns of the music notes to retrieve songs [34], and introducing new features from music objects to recognize music information such as music themes [35]. In their work, [35] emphasized the notes to locate patterns that reappeared more than once in a song and they agreed with [33] descriptions about the rhythm contents which can be used symbolically to recognize a certain pattern of a song.

This can be very useful in the music identification process especially songs that can be recognized using the themes or stories.

Pitch. In music, pitch is normally associated with a high or a low tone, which depends on the frequencies or vibration rates of a music sound. A frequency is the number of vibrations per second and is measured in Hertz (Hz). A high frequency means high pitch and a low frequency means low pitch. The high or low pitch of a tone in a sound note is the listener's evaluation of the frequencies.

Two different methods of extracting pitch contents were presented, where one focused on the phrase-based melody extraction [36] whereas the other used mathematical computations to extract the contents from the music signals [3] [37] [38][39].

In the first method, [36] focused on relative pitch sequences that were obtained by converting the song notes to different levels of pitch, which is higher than, or equal to, or lower than the previous note.

The second method used a computationally mathematical model to extract the pitch contents from the complex audio signals. The computation involves an autocorrelation tool that is useful to find repeating patterns in a signal. This tool is used to determine the presence of a periodic signal that contained noise and to identify the fundamental frequency of a signal. [38] was the first to mention the proposed method, called auditory model to compute a multi-pitch analysis model considering an auditory modelling point of view.

A recent study that adopted the auditory model is in [39] where the author compared the pitch analysis content using an auditory model and conventional methods of obtaining the pitch contents. The study showed that the auditory model has greater advantages than the conventional techniques in obtaining the pitch sequences using the frequency-related analysis. Following the work of [38], [37] applied similar technique to extract the pitch contents from the music signals.

3.2 Music Feature Selection

The music representations used a wide set of extracted features from various music contents, such as timbre, pitch and rhythm. Among the features, some are irrelevant and redundant for music recognition processes. These irrelevant and redundant features need to be eliminated before we use the rest of the features in recognition processes. The reason for the elimination is that, music recognition can improve the classification performances and shorten the processing [40]. Selecting the relevant features from a wide range of extracted features is a challenging work [41]. The term relevant as applied in the literature normally depends on the question of relating the relevancy of features to something else [42].

3.3 Music Genre Classification

In this stage, we introduced the Modified AIS-Based Classifier that contained two important modules of Negative Selection Algorithm (NSA) which are the censoring and monitoring. Censoring is a process where detectors are generated, and monitoring is a process where comparison between detectors and antigen are made to find the match. Modified AIS-based classifier is proposed after some modifications and adjustments are applied to the NSA. These works are important in our research as it is to enable the proposed classifier to solve the music genre classification problem. Figure 2 shows the building blocks of the proposed classifier in this last stage of the classification framework where three important mechanisms of NSA is illustrated, which are the binary bit string conversion, censoring and monitoring modules.

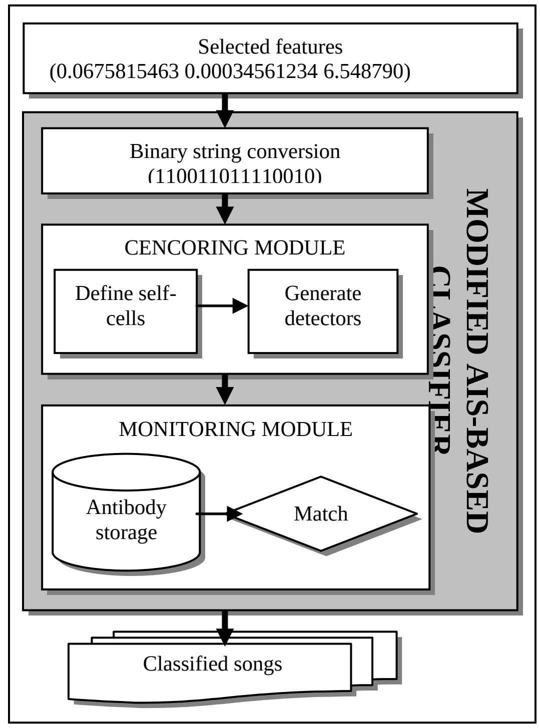

Figure 2. Stages of classification task involving censoring and monitoring modules

Censoring This module is described as a module that produces detectors, which is the key aspect of identification. Censoring module normally starts after feature extraction and feature selection finished. It involves data features conversion where the features will be represented by binary strings (for example, feature vector = -3.4523123 is converted using –XOR operation and becomes 101011001). After the conversion, the binary strings will then go through the complementary process and become the detectors.

The detectors are created based on how many song genres that are needed to be classified. During the process, antigens are compared with the detector candidates to evaluate the affinity binding (similarity values). The process applies the XOR operation to determine and evaluate the affinity binding between them. The threshold value is used as a benchmark in the process. As each antibody is consisting of 15 binary digits, the threshold value is set to a certain value in order to evaluate the affinity binding between detectors and antigen (song genres). In the XOR operation, values “0” and “1” are used and are counted to decide whether the matched bits exceed the threshold value or not. As the algorithm considers the non-self cells as detectors, the not match antigen-detector will be based on the “1” value. The higher the “1” than “0” value during comparison, more non-self cells are indicated. Once identified, the cell then is considered as a detector and is stored for further analysis in the next module. The detectors are generated from the training data where in the process, a training model is created and used in the identification and classification processes.

Monitoring. This module starts once the detectors (training model) are created and are compared to the antigens (we used testing data as antigens) to find similarity between these data and calculate the affinity binding. The comparison is referring to the classification task and when it produces binary bit ‘1’, the data is considered bind. However, in this scenario, we will use the word ‘match’ instead of ‘bind’ to define the similarities. In the original version of NSA, the process uses value “0” to indicate similarity or ‘match’ during monitoring process. The more of ‘0’ found, the more similar the antigen to the detector. Once matched, the antigen is considered as self cell and will be ignored. Since the objective of NSA is to identify non-self cells to recognize antigens, the ‘non-match’ cells are detected and a change situation is assumed occurred in the network security.

The comparison of value ‘0’ is simple and straightforward however, according to [43], the term ‘match’ as used in the original version of NSA did not give any specific meaning, it is too general, and did not specify the type of representation space used.

Another important factor in the monitoring module is the threshold value. The value is used to set the benchmark number of binary bits that both antigen and detector cells should bind, because it will decide whether they are matched or not. Both cells are considered matched if the bind bits are exceeding the threshold value. The value used in the experiments generally indicates the reliability levels of the results where the higher the value used means reliable results are obtained from the similarity matching process.

Classification accuracy. In the proposed modified AIS-based classifier, we combined all feature vectors from the music contents (pitch, rhythm, and timbre contents). Table 1 discusses the computation stages, where the first stage of calculation is applied to identify and compute the bits between both cells that are matched and then get the match percentage. In the next stage, the calculation is to get the threshold value percentage where the value will be the indicator used to decide whether each dataset is matched or not. The last stage of calculation is to get the classification accuracy where all matched song are divided with the amount of total tested data and then get the percentage.

Table 1. Proposed classification accuracy method

Category	Calculation formulas
Data genre accuracy stage	Σ bits_matched / Σ features_bits x 100
Threshold (r) %	(Σ r * num_of_features / Σ bits_per_feature * num_of_features) x 100
Dataset accuracy stage	(Num_of_genre_match / num_of_testing_data) x 100

Four binary matching techniques are applied in the AIS, which are the Hamming distance matching, the r-chunk matching, the r-contiguous matching and the multiple r-contiguous matching rules.

4 EXPERIMENTAL RESULTS

The songs that we used in our experimental work comprises of ten different genres in the Western song collections, which are Blues, Classical, Country, Disco, Hip-hop, Jazz, Metal, Pop, Reggae, and Rock. One thousand songs (courtesy of MARSYAS group research) are used in the experiments. Two applications were used to extract these features, which are MARSYAS [44] and rhythm pattern extraction tool [45].

We prepared training and testing datasets where similar data is used in the experiments except the data is in the attribute related file format (ARFF) for WEKA experiments and in the data file (DAT) format for modified AIS-based classifier demonstrations. Two attribute evaluators are the CFSSubsetEval and the ConsistencySubsetEval which apply both BestFirst and GreedyStepwise search are used to select significant features in the experiments. The selected features are tested separately in the classification experiments to find which significant selected features produce the highest classification accuracy.

We evaluate the proposed AIS-based music genre classification algorithm based on the results produced in the classification experiments using our proposed modified AIS-based classifier and WEKA application. We have conducted the experiments using classifiers from WEKA application such as the k-nearest neighbour learner, decision tree, support vector machine and naive-bayes. The tested classifiers are the bayes-net, sequential minimal optimisation (SMO), IB1, J48 and Bagging.

Two setup cases of experiments were prepared, which are according to the binary similarity matching techniques, and the feature selection techniques. The classification performances are evaluated according to the classifiers used in the experiments. The music contents are individually classified in the classification evaluation. From the three contents, the music features that we have extracted are categorized into five main groups:

1) timbre-related features consisting MFCC, zero-crossings rate, spectral centroid, spectral flux, and spectral roll-off,
2) chroma-related features consisting 12 music notes (A, A#, B, C, C#, D, D#, E, F, F#, G and G#),
3) rhythm pattern (RP),
4) rhythm histogram (RH), and
5) statistical spectrum descriptor (SSD) features

The following figures illustrate the classification results according to the setup cases.

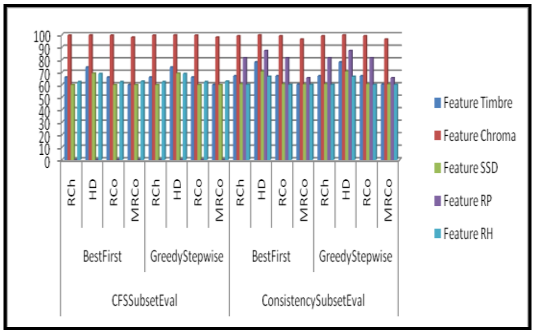

Figure 3. The classification performances of modified AIS-based classifier using different binary matching techniques

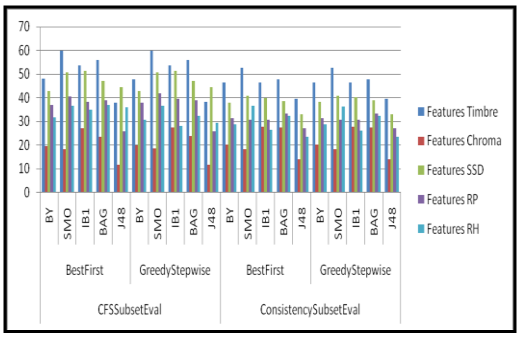

Figure 4. The classification performances of WEKA classifiers

Figure 3 and 4 illustrate the performance of classification experiments using various similarity matching techniques (R-Chunk (RCH), Hamming Distance (HD), R-Contiguous (RCo) and Multiple R-Contiguous (MRCo)) in the modified AIS-based algorithm and classifiers in WEKA application. Both feature selection techniques, CFSSubsetEval and ConsistencySubsetEval are compared in the performance evaluation. Overall, we can see that the results from the proposed classifier averagely are higher than WEKA classifiers by 20 – 30 percents. Among the matching techniques, HD technique has consistently produced classification accuracies between 70 – 90 percent when evaluated with the feature vectors selected using the Consistency SubsetEval technique.

5 CONCLUSIONS

The availability of techniques and methods for classification in music analysis field today has shown that researchers in this area are very concerned with the performance. As the collections of digital songs keep increasing online, their studies have contributed a major breakthrough to the internet users and others.

In this paper, we have explained and evaluated the proposed modified AIS-based classifier in different category of experiments. In each experiment, the proposed classifier outperformed any performance from other classifiers. The classification results clearly show that the proposed modified AIS-based classifier is a new algorithm or mechanism to solve problem in the area of music genre classification.

We strongly believe that our discussion throughout this paper has given opportunities to other researchers in this area of studies to fill the gaps, to explore further and to provide solutions to the known and un-known problem that has yet to be discovered. Future work will include an investigation on how to manage the threshold value efficiently and probably, exhaustive search approach should be applied to evaluate the highest threshold value that can provide high classification accuracies.

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