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Towards Automation and Classification of BharataNatyam Dance Sequences

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BharataNatyam (BN) is an ancient Indian Classical Dance (ICD). Creativity and innovation are the soul of any art including BN dance. Within the framework of rules and traditionally accepted boundaries, choreographers try to innovate and create unseen, aesthetic and novel BN dance sequences. The human efforts can be supported with the computational assistance to generate valid, genuine BN dance sequences. Moreover, these movements can be empowered by the unspecified rules extracted from the analysis of "Adavus", which are considered ideal BN dance sequences for "Nritta" or pure dance movements. Thus an altogether new and interesting sequence can be obtained.

In this paper we present our experimental ArtToSMart (System Modeled art) system, which gradually enhanced from one beat dance pose generation to 'm' beat dance sequences generation comprising of 'm' system generated dance poses. Furthermore, we are tagging these sequences with the help of BN dance experts and trying to develop a machine learning model to classify system generated BN sequences. The use of Rough Set tools have proved to be impressive for the same.

Keywords: Dance Automation, Dance Modeling, Evolutionary Approach, BharataNatyam, Choreography, Classification,Rough Set Theory, RSES.

1. Introduction

BharataNatyam (BN) is an ancient Indian Classical dance form originating from the temples of South India.It was described by the manuscripts namely "Natyasastra"

(NS) and "Abhinayadarpana" (AD) which are the only source of documentation for this Classical dance form. BN has become the most widespread and popular of the Indian classical dance forms. It has achieved international recognition as one of India's treasures.

A traditional style of BN dance is practiced for many years together through the guru-shishya parampara (traditional learning method from a teacher). A BN dancer gains perfection by practicing the same moves for many years. Thus most of them would prefer choreographing a sequence from what they have already learnt since its the muscle memory which remains prevalent. The additional efforts required for altogether new moves are generally avoided for various reasons like avoiding criticisms, commercial aspects and so on. Our work is involved in this domain. We would like to use some novel choreographic patterns which are in sync with the traditional norms but unpracticed and unheard of. We propose to do it using analysis of domain knowledge and power of Information Technology. So far we haven't come across automation for the choreographic process. Although Choreography is an art which most of the people staunchly consider as a human domain, we have attempted to use a computer to automate the process of choreography for pure dance movements called as "Nritta" in BN. Using the power of Information Technology, an attempt has been made to aid the choreographer in this creative process. Hence we have named it as ArtToSMart where SMart means System Modeled art.

BN is clearly divided in the rule books of dance into two categories: Nritta (pure dance movements) and Natya (movements with expressions). We have focused our research to the pure dance movements only. These movements are easy to learn even for a beginner and generally the same set of steps are followed and taught to students depending on the school of dance. Most of the body movements are clearly defined in the ancient scriptures namely NS and AD.The art of storytelling (Natya) through dance or conveying meaning for a lyric is comparatively easier once a dancer has mastered the technique. We noticed that almost all the experts and practitioners use the same kind of choreographic patterns for the pure dance movements. Innovation in this area is hardly attempted.Thus creating unique choreographic patterns only for aesthetic purpose, with coordinated hand and leg movements (referred to as adavus) becomes a more challenging aspect. We have attempted to generate unique moves for these rhythmic pure dance movements since this challenge is rarely experimented by the traditional and modern practitioners.

We introduce our ArtToSmart system that use evolutionary approach to obtain novel and genuine BN dance poses for pure dance movements. All these system generated dance poses are in accordance with the BN dance rules and still exhibits novelty. Several dance experts have seen the system and appreciated the dance poses generated by the system. However, our main focus in this paper is to elaborate how the ArtToSMart system is enhanced to obtain multibeat BN dance sequences. We want to develop a classifier system to tag each sequence generated by the system. The details thereof are presented in this paper.

The Paper is organized as follows. Section 2 discusses related work in the field of ICD, section 3 puts forth the details of the basic ArtToSMart system. Enhancement of the system to generate continuous BN dance sequence is explained with the help of generic framework and by demonstrating the user interface in Section 4. Conclusions are presented in section 5 whereas how we plan to incorporate machine learning techniques to build a classifier model is discussed in Future Work section 6.

2. Related Work

Translated versions of NS [Ghosh (1951)] showed that the major limbs of the body are very clearly defined for its movement definitions. A combination of all these major limbs of the body like: head, hand, waist and leg movements showed the enormous amount of possibilities in lakhs for a single beat movement [Jadhav S and Sasikumar M (2010)]. Thus to get the system to choreograph, all the possibilties, modelling of the human body had to be done. Jadhav et al. [Jadhav S, Joshi M, and Pawar J (2012a)] have used a thirty attribute dance position (*dp*) vector for identifying a dancers pose at the end of a beat. This *dp* vector shall portray the position of a dancers major limbs like head, right hand, left hand, waist, right leg and left leg. This helps to capture every frame of a dancers movement. With the help of this *dp* vector Jadhav et al [Jadhav S, Joshi M, and Pawar J (2012b)] have designed an unique fitness function which will help an expert choose the best possible moves from amongst several available for a single beat. Experts have evaluated these system generated moves and on an average, the expert reports show that all the poses are acceptable and unique from the existing adavus(which are considered the traditional pure dance movements). The measurement of the goodness of the dance pose was itself a challenging task and hence we proposed a unique method for doing this through an evolutionary approach [Jadhav S, Joshi M, and Pawar J (2012b)]. Such type of fitness function was evolved for the first time for Indian classical dance which had variables like vector difference and limb variation count.

Several researchers have attempted to use various classical dance forms of India for animation [Pattanaik S (1989)], heritage preservation [Mallik A, Chaudhury S, and Ghosh H (2011)]; e-learning [Hariharan D, Acharya T, and Mitra S (2011)], notating [Karpen (1990)] and mobile applications [Majumdar R and Dinesan P (2012)] but we havent encountered any research work so far in the field of choreography for Indian Classical Dance. Our approach of modeling the human body for dance poses representation as well as new dance pose generations is altogether different. Encouraged by experts with the results obtained for single beat, we have attempted the same for multi-beat choreography.

3. Art To SMart system

The ArtToSMart system has two major components namely BN Dance Modeling and BN Dance Choreography Automation as shown in Figure 1. Both modules

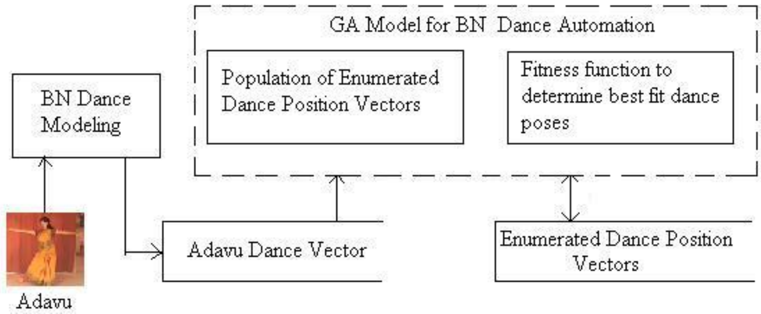

Fig. 1. ArtToSMart system generic framework

are elaborated in following subsections. The results obtained are evaluated by the experts and presented in subsequent subsection.

3.1. *Modeling BN Dance*

Any BN dance position is a manifestation of one of the possible combinations among legitimate poses of various body parts. Hence, in order to model different BN dance positions we must represent the exact positions of the six major limbs of the body (head, hands, waist and legs) at each step. We identified different set of attributes to model the different body part positions. Hence, a dance position vector (*dp* vector) can be defined as a combination of all these attributes that in totality represents a single BN dance position at the end of every beat. We have used eight attributes each to model each hand position and five each for each leg position. In addition, we have considered two attributes each to model head and waist movement. Thus, the *dp* vector is a thirty attribute vector that corresponds to a dance position. Body part positions can be visualized and modeled using the orientation of a body part or its subpart from specified X, Y and Z axes [Nakazawa *et al.* (2002)]. For further details of all of the codification process refer [Jadhav S, Joshi M, and Pawar J (2012a)].

We represent the dance model as follows.

$D =< L_{hd}, L_{rh}, L_{lh}, L_w, L_{rl}, L_{ll} >$, where L_i represents a set of attributes that correspond to exact position of a limb in that dance step. There are two attributes each for head and waist, five attributes each for left and right legs, and eight attributes each for left and right hand.

Any dance step attribute can be referred to as $D_i.a_k$ or $L_i.a_k$, where i refer to a dance step or one of the limbs and k refers to any one of the thirty dance vector attributes corresponding to a certain limb. So $D_1.a_5$ refers to an attribute that corresponds to right hand. The same attribute can also be referred as $L_{rh}.a_3$.

Fig. 2. A sample BharataNatyam dance step.

Table 1. Dance Vector Description

Limb	Generic Dance Vector attributes	Limb attributes for Dance Step of Figure 2
Head	$L_{hd} = \{a1, a2\}$	$L_{hd} = \{2, -1\}$
Right Hand	$L_{rh} = \{a3, a4, a5, a6, a7, a8,$ a9,a10}	$L_{rh} = \{0, 2, -1, 1, 3, -1, 0, 0\}$
Left Hand	$L_{lh} = \{a11, a12, a13, a14, a15,$ a16,a17,a18}	$L_{lh} = \{0, 4, 0, 0, 1, -1, 0, 0\}$
Waist	$L_w = \{a19, a20\}$	$L_w = \{0, 0\}$
Right Leg	$L_{rl} = \{a21, a22, a23, a24, a25\}$	$L_{rl} = \{0, 0, 1, 0, 0\}$
Left Leg	$L_{ll} = \{a26, a27, a28, a29, a30\}$	$L_{ll} = \{0, 0, 0, 0, 0\}$
Complete Dance Vector for Figure 2 $[2, -1, 0, 2, -1, 1, 3, -1, 0, 0, 0, 4, 0, 0, 1, -1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0]$		

The dance step[a] of Figure 2 is represented using the dance vector shown in Table 1.

3.2. *BN Dance Automation*

We used Genetic Algorithm (GA) to determine appropriate BN dance steps.The formulation of an appropriate fitness function is our key contribution besides modifying crossover and mutation operation to suit the problem domain.

Both crossover and mutation operations are modified to suit to the application. Each dance vector itself consists of representation of six limbs. Hence each gene g_i is a combination of six subgenes. The crossover operation is performed for all

[a]Courtesy: www.onlinebharatanatyam.com.

subgenes at subgene level only because values in all subgenes have different range of values. Hence for one pair of genes the crossover operation resulted in six pairs of genes. The system can be experimented with different crossover start points in all the six subgenes.

Determination of a fitness function is the most critical and important task in the development process of any GA based system. The objective of the fitness function of the proposed system is to carry forward appropriate dance steps from a set of enumerated dance steps of a GA generation to the next generation. We wish to generate dance steps that are not too far or too close (identical) to the adavus [Jadhav S, Joshi M, and Pawar J (2012b)]. Hence, our fitness function is based on distance from adavus. The fitness function involves two parameters namely limb variation count (LVC) and absolute vector distance (AVD) to determine the distance from ideal dance steps. More details of the parameters used are as follows.

LVC: It gives the counts of body parts that are distinct in two dance vectors (six major limbs of the body are represented by a dance vector). For example, if we have a change only in hand position between two chromosomes and the rest limb positions are exactly the same, then the limb variation count would be 1 and so on. More is the value of LVC, further apart are the two dance vectors from each other.

AVD: This parameter gives the absolute distance between two dance vectors. It is a cumulative sum of differences between the corresponding values of the thirty attributes of two dance vectors.

The distance 'd' is a function of AVD and LVC.
d = f(AVD,LVC) = $(0.75 \times AVD) + (0.25 \times LVC)$
We have given higher weightage (0.75) to AVD over LVC (0.25) since the more the vector difference, more is the variation and novelty to the new dance step and lesser the limb variation, lesser will be the deviation from the ideal dance step. Expected behavior of our proposed fitness function is a bell shaped curve which is a normal distribution curve.

Fitness function value (ffv) is given by, ffv = f(d) = ND(d), where ND gives normal distribution of the distance. The normal distribution ensures that higher fitness value shall be assigned to the dance vectors that are not too close or not too far from the ideal vectors. More details can be obtained from [Jadhav S, Joshi M, and Pawar J (2012b)].

3.3. *Results Evaluation*

We have obtained various results from the GA driven system for a single beat. These results were in the form of a vector and to analyze and interpret the same, we had to draw manually the corresponding stick figures for each of these vectors. Later on these vectors were explained with the help of the stick figure to our dance expert who posed for them and pictures were clicked accordingly. These results were shown to various dance experts and they were requested to fill up a tabular format questionnaire with ratings ranging from 1 (Worst) to 5 (Excellent). This evaluation

Fig. 3. A 3 beat BN dance sequence with no leg movements.

was utilized in the form of Mean opinion score (MOS).

MOS is a technique to obtain subjective feedback about image quality from experts. We consulted several domain experts from Goa and Pune to rank the results generated by our system. The images are ranked on a scale of 5 as follows:

1 : Not acceptable, 2 : Bad, 3 : Ok, 4 : Good, 5 : Excellent.

Our results show that 13 of the images are rated as Ok, 5 as Good and 7 as Bad out of the 25 images given to 5 different experts of BharataNatyam from Pune and Goa. None of the expert rankings through MOS has been rated as Not Acceptable for these 25 images.

4. Multibeat Choreography

In order to enhance the ArtToSMart system to generate multi-beat BN dance sequences we upgraded our model as shown in Figure 4. It shows overall architecture of the multi-beat sequence dance generator system including modules for dance representation and an evolutionary module for single beat dance pose generation. Rule generation module and multi-beat choreography generation module are the newly added modules. Following subsections elaborate both new modules.

4.1. *Rule Generation*

Rule generation module analyzes the ideal BN dance sequences including Adavus. The analysis formalizes certain rules in terms of LVC and AVD metrics to determine consecutive dance poses in multi-beat sequence. Some of these rules are derived from dance experts while several others are resulted through detailed analysis of Adavus.

Figure 3 shows a three beat dance sequence. In this test case, the dance poses are OK but not acceptable to teachers since there are no movements of feet. Hence, we need an appropriate LVC related rules.

An extensive analysis of several Adavus besides the advice of domain knowl-

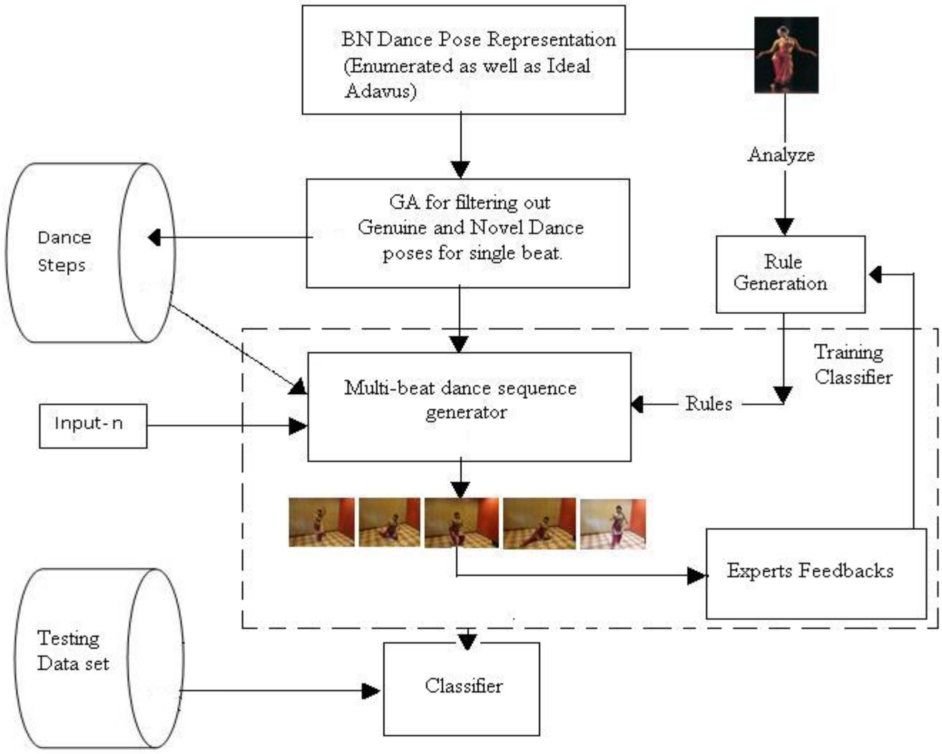

Fig. 4. Multibeat Dance Generator Module.

edge experts yielded several rules that are incorporated in the system. Some of the observations are as follows.

(1) LVC between any two consecutive dance poses is more than 2.
(2) In most of the cases LVC between any two consecutive dance poses is 3 or 4.
(3) For m beat sequence LVC in all consecutive dance poses is more or less consistent.
(4) At least one leg movement is present in any two consecutive dance poses.
(5) AVD measure between consecutive dance poses do not have large variations.

A sequence of m dance poses can be considered for choreography if it satisfies certain constraints. Adavus are considered to be ideal dance moves for pure dance movements [Majumdar R and Dinesan P (2012)]. Hence they serve as good reference points for generating choreography. The filters/constraints identified to be applied to simulate adavu patterns according to various rules generated. Some of the filters/constraints are as follows.

- Hand Mudra Filter: One of the most striking aspects of BN is its intricate

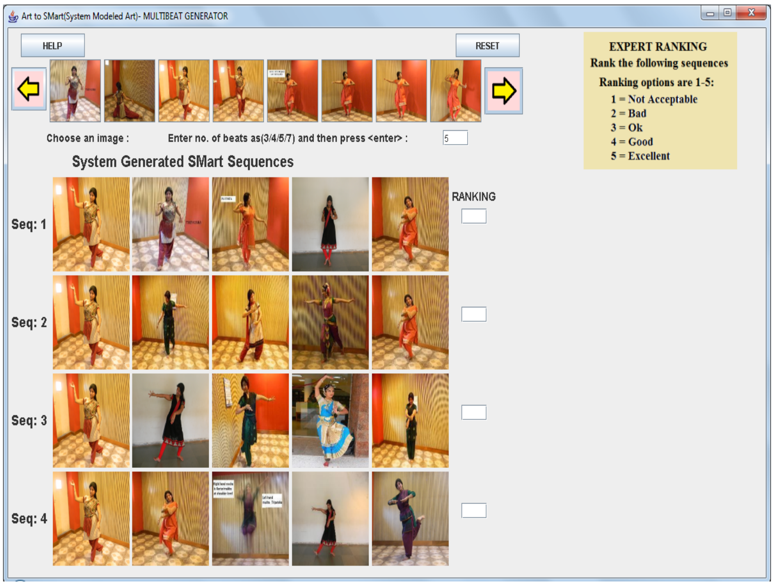

Fig. 5. Snapshot of 5 beat Dance Generator Module.

hand gestures.These are significant in order to convey the meaning of what a dancer is performing with the help of facial expressions. However, there are also Nritta Mudras, that are employed for the sake of beauty and decorative purposes while performing Nritta. A dancer does not keep changing mudras for every consecutive beat and there are several restrictions as to which mudra can follow the other. Thus our system too needed to have these constraints embedded in them.

- Leg Filter: A multi-beat movement generated without any leg movement appears stationary as can be seen in Figure 3. Thus it is absolutely necessary for the leg movements to happen.
- Fitness Function Value Filter: The main task of the GA driven system is to find the best possible chromosome with the help of an appropriate fitness function.This is calculated on the basis of 2 parameters namely Absolute Vector Difference (AVD), and Limb Variation Count (LVC). The single beat choreography results were based on the same parameters [Jadhav S, Joshi M, and Pawar J (2012b)] and we have reproduced the same for continuity in multi-beat results also.
  Absolute Vector Difference: A dance pose with least AVD is found to give good representation for the population since it's the closest to the earlier *dp* vector.
  Limb Variation Count: Consistency in LVC value across the poses increases the aesthetics of the dance sequence generated.

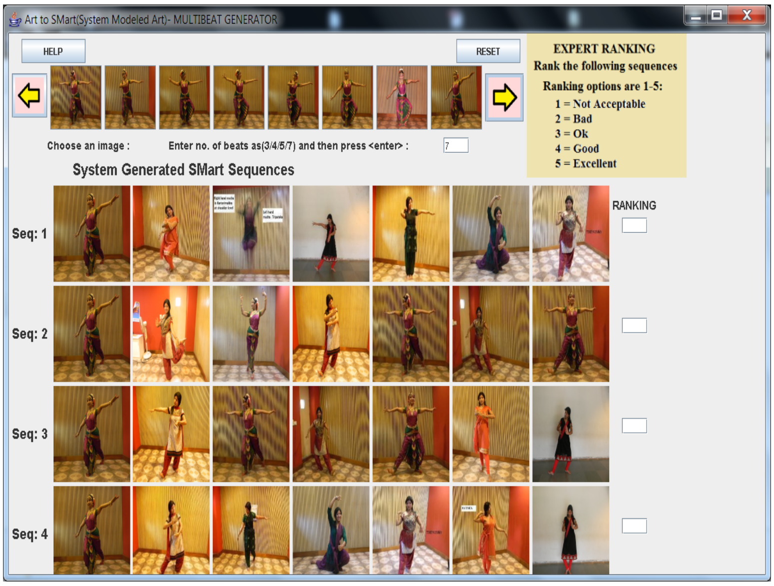

Fig. 6. Snapshot of 7 beat Dance Generator Module.

4.2. *Multi-beat dance generator*

Let P= $p_0, p_1, p_2, p_3, ...p_n$ be the set of all the feasible single beat dance poses generated using the ArtToSMart system [Jadhav S, Joshi M, and Pawar J (2012b)] and stored in a database for further usage. Each p_i is a 30 attribute dp vector. An interface is developed to generate a m beat dance sequence comprising of genuine dance poses available in the database. The multi-beat generator allows user to pick up the starting pose and generates ten different m beat BN dance sequences. Every subsequent dance step in all these dance sequences is derived using all rules obtained in rule generator module. Two snapshots for 5 beat (Figure 5) and 7 beat (Figure 6) BN dance sequences are shown to elaborate the working of multi-beat generator.

Initially the user is asked to enter the number of beats for which choreography is to be generated. The enhanced ArtToSMart system iteratively chooses best suitable dance position vector from among the database with the help of Rule generator module. The rule generator module keeps on upgrading itself by the means of expert's ranking.

The experiments have been carried out using an Intel Core i7 Processor with 4GB RAM for our experiment purposes. The Operating System used was 64 bit Windows 7, JDK 1.7, MyEclipse 7.1, My SQL Workbench and XAMPP server for the development of the Java code.

5. CONCLUSION

The ArtToSMart system is discussed and the BN dance poses(for single beat) as well as BN dance sequences(for multiple beats) generated by the system are presented. An opinion by most of the dance experts has been that the results are good enough to evoke the creativity process for unique choreographic sequences. The poses shown by the system for a single and multi-beat are unique and can help a teacher to teach their students new sequences or let them explore the choreographic process by asking them to run the system with different parameters and starting poses. Thus for promoting and evolving BN an unique attempt has been made by using the power of Information Technology for an ancient Classical dance form of India.

6. FUTURE WORK

We are in the process of development of a classifier to automatically classify any system generated dance sequence as described in Figure 4. As shown in Figure 4, we have identified training and testing datasets separately. Training dataset shall be obtained by requesting the domain experts to rank(tagging) the resulting dance sequences as shown in one of the interfaces (Figure 5 and 6).

Rule generation module must capture more number of implicit as well explicit rules in order to ensure better dance sequence outputs.

The ArtToSMart system generates several enumerated dance poses every time. To automate the task of classifying these dance sequences and also for the best feature selection, we have used Rough Set Exploration Tool; RSES 2.2.2. We have designed 30 attribute dp vector for depicting the dance poses.Thus our aim is to reduce these attributes to a minimal subset. We also need to retain high accuracy while determining a feature selection method in the field of BN. This shall help us in data analysis and determination of the most important attributes from amongst these thirty dp vectors. Hence 224 trained instances (validated by domain experts) were given to the system and reducts were obtained. The generated size of the reducts were 7 and 8 respectively. After carefully analyzing these results of the reducts, we found that the system was choosing one attribute from the head, at least 3 from the hand which consists mainly of the mudras of both hands and wrist position, one from the waist and remaining 3 from the leg. This needs to be studied in detail to know whether only 7 or 8 attributes are enough to identify the dance pose as compared to the earlier 30 dp vector. One thousand eight hundred and sixty six rules were generated by the system. A study of these rules show that Class 1 termed as OK has 535 rules, Class 2 termed as Good has 255 rules, Class 3 termed as Bad has 130 rules and Class 4 termed as Excellent has 946 rules. After filtering out the rules with support ranging from 1 to 1 and so on we get the rules of the required match. We notice that the highest matches occurring 11, 9, 5 and 4 times from amongst these rules are having Class 4 because they are from the Adavus which are ideal dance poses. Hence we need to identify and study all the other rules with different classes for identifying the best possible pose. Using crossvalidation method, the system has generated 72.7 percent accuracy for the trained data. These rules can be evaluated to find the best possible decision making system for the classes. This will help in automating the process of Machine Learning for better decisions. The system can be trained further to get more accuracy and later be tested with the enumerated data. Similarly we intend to try out the experiments with another Machine Learning tool called WEKA and compare the results of both the systems. Experts from the domain can validate the results and hence we can get a robust choreographic tool for BN.

7. ACKNOWLEDGEMENTS

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