Art to SMart: An Evolutionary Computational Model for BharataNatyam Choreography

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***Abstract*—Dance choreography is an intense, creative and intuitive process. A choreographer has to finalize appropriate dance steps from amongst millions of possibilities. Though it is not impossible, the choreographer being human cannot explore, analyze and remember all these variations among steps due to large scale of available options. Hence, we propose to simplify the problem of exploring and selecting dance steps from amongst the huge set of all possible variations for an Indian Classical Dance, BharataNatyam (BN). Based on a computational model developed by Jadhav et al. [13], we propose a Genetic Algorithm (GA) driven automatic system that would provide a list of unexplored novel dance steps to choreographers. We have incorporated certain measures to ensure that the proposed dance steps should be feasible and appropriate.**

In this paper, we discuss an automated approach to obtain unexplored dance steps using a proposed fitness function for a single beat/count. The details of experimental study performed for the Genetic Algorithm based art to SMart (System Modelled art) system along with the results obtained are also presented in this paper.

I. Introduction

Any dance form, can be conceptually decomposed into its constituent base movements, involving specific positions of body parts and the norms for combining them. The combinations are constrained by physical constraints, aesthetic constraints, preferential constraints, etc. Treatises like Bharatmuni's Natyashastra and Nandikeshwara's Abhinayadarpana codify such constraints and rules in a human experience and existing literature. BharataNatyam (BN) is an ancient Indian Classical Dance form, well documented in the scriptures and it has classification of elementary body movements like head, eye, neck, hands and leg movements. BN also classifies dance into Nritta i.e. rhythmic dance movements/ pure dance movements, used for aesthetic purposes in dance and Nritya i.e. representational dance which conveys a meaning. Our focus of research is only for assisting in choreography of Nritta and this paper focuses on movements only for a single beat/count.

The choice of only Nritta for choreography is as follows: for any given song, it's easy to choreograph the lyrics of the song since it has meaning but the portion in between the two stanzas of a song mostly has music. A choreographer always finds it a tough task to choreograph this part. Either she/he can choose to choreograph this piece with some meaning conveyed e.g. show the dancer waiting for her beloved or search for him, etc or use some beautiful, intricate dance steps which has no meaning but which will add elegance to the dance.Our work shall aid the choreographer in choosing the best dance steps for Nritta.

A Simple Java Program developed to automatically generate the movement combinations possible for a single beat shows that the choreography combinations are lakhs in numbers for even a single beat [14]. Thus we can realize that the problem is having a large search space for a choreographer and although they have good expertise in their subject of dance, no human being can remember and analyze all of them simultaneously. Thus while the generated sequences are exponential in nature, it becomes extremely difficult to enumerate them and classify them manually.

Furthermore, it must be noted that we are not merely working on enumeration problem. We are striving to obtain dance mudras that takes into account dance aesthetics (Limb variation) in conformance with the classical BN dance (Adavus). Hence, we propose a GA based automated system to identify unexplored dance combinations. 'How to measure the goodness of a dance mudra?' is itself a challenging task. We propose a fitness measure that assists to select good dance mudras and passes them to next generations to ultimately obtain results that are approved by well known BN dance performers.

Our paper throws some light on how a choreographer can use a machine to help him/her to select the best possible dance step combinations. This paper is organized as follows - In Section 2, we describe the related work done till date in this area. Section 3 has four subsections and explains in detail about the process to generate unexplored dance steps. Section 4 explains the results obtained and is followed by conclusion and future work in section 5.

II. Related Work

Automating dance choreography and capturing the movements have been done previously. Dance Representation can be done using existing notation. Ebenreuter [9] has attempted to design an interface to facilitate the exact documentation of dance notation while in her paper Karpen [15] has tried to solve the problem of notation for Bharata Natyam by using Labanotation. LabanDancer

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system developed by Calvert et. al [6] helped to translate the recorded labanotation scores into 3-d human figure animations. Choreographic process was enhanced by Nahrstedt et. al [18] using a 3D tele-immersive (3DTI) room surrounded by multiple 3D digital camera and a remotely placed dancer with a remote 3DTI room in a joint virtual space. Laban Movement Analysis (LMA) provides a model for observation, description and notational system for human movements. Implementation of the same in a computer has been done through Bayesian approach [22] and also by 3DTI [18]. Choreographic Language Agent (CLA) [7] helped to bridge the gap between the notations, sketches, diagrams and text done by the choreographer on a notebook and his thinking process. Thus a unique method was used to augment the thinking process of the choreographer. Based on Newton's Law Hseih et. al [12] generated a dynamic model according to dance verbs jump, flip, etc.

Capturing and modelling of all the dance movements correctly results in efficient processing too. Several attempts have been made by researchers in various ways to process these captured and modelled data. Some of them are Evolutionary approaches using Genetic algorithms [20], [16], [10] and Multi agent system [2], [8] optimization Algorithms, Classification using Neural networks [21] and Support Vector Machines [10], Image Processing for gesture recognition [11], [3], Graph based algorithm with Probabilistic and statistical model [3], [1], [4], [19], [22], Corpus Based [1] and using Multi agent system [2].

The Art to SMart system differs from the existing work since it is focused in the area of Indian Classical dance, BharataNatyam and the system is generating novel steps through evolutionary programming and is a tool for the choreographer to enhance his skills.

III. Evolving Unexplored Dance Steps

Our objective is to suggest choreographers a list of dance steps that are possible but yet unexplored. Our attempt has been to try and not to deviate much from the original traditional style. As mentioned earlier, we have used GA to determine the appropriateness of the dance steps that must be filtered out from among lakhs of possibilities [14]. *Appropriateness* is modelled by a fitness function and we propose the fitness function that determines the distance of generated dance steps from what are supposed to be ideal dance steps in BN. In following subsections, we first elaborate about ideal BN dance steps followed by our dance representation model and the fitness function.

A. Ideal BN Dance steps

"Adavus" in BN are the fundamental unit used in nritta where hands, feet, head, eyes and other parts of the body move in a co-ordinated manner. These are considered as excellent moves [17] for any given number of beats. All the basic dance movements of pure dance are organized into a progressive series of lessons which are the adavu chapters. Each adavu (basic unit of motion) is taught in systematic order and then combined with others to produce choreographed sequences based upon the rhythmic contour of a musical composition.

Figure 1. A sample BharataNatyam dance step.

From above we can conclude that Adavu is an excellent movement for Nritta and hence can be considered to be ideal for comparison of movements. We have represented these dance steps using our dance step representation vector model in [13]. A brief description about this model is given in the next subsection as a ready reference.

B. Dance Steps Representation Model

We represent each BN dance step using 30 explicitly derived attributes which capture six important major limbs (head, hands right and left, waist, right and left leg) [13] A dance step is represented as a dance vector. The dance vector has 30 attributes and these attributes represents exact position of six major limbs that comprise a dance step. 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 $L_{rh}.a_3$.

The dance step[1] of Fig. 1 is represented using the dance vector shown in Table I.

We modelled Adavus using the dance vectors. A java program generated random dance positions that were used as an initial population for the GA driven system. The details of the GA used for the proposed system are presented in next subsection.

C. GA for the proposed art to SMart system

This subsection contains some of the basic concepts of genetic algorithms as described in [5]. A genetic algorithm is a search process that follows the principles of evolution through natural selection. The domain knowledge is represented using a candidate solution called an *organism*. Typically, an organism is a single genome represented as a vector of length n:

$$g = (g_i \mid 1 \leq i \leq n), \qquad (1)$$

[1] Courtesy: www.onlinebharatanatyam.com.

Table I
DANCE VECTOR DESCRIPTION

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

Input:
Population: The number of organisms to be generated,
Generations: The number of successive populations to be generated,
Output:
A set of dance steps that are evolved through and having better fitness value.
Steps:
generate initial population, $G(0)$;
evaluate $G(0)$;
for (t=1; $t \leq generations$; $t++$)
generate $G(t)$ using $G(t-1)$;
evaluate $G(t)$;

Figure 2. Genetic Algorithm used for the art to SMart system.

where g_i is called a *gene*.

A group of organisms is called a *population*. Successive populations are called *generations*. A generational GA starts from initial generation $G(0)$, and for each generation $G(t)$ generates a new generation $G(t+1)$ using genetic operators such as *mutation* and *crossover*. The mutation operator creates new genomes by changing values of one or more genes at random. The crossover operator joins segments of two or more genomes to generate a new genome.

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 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.

Fig. 2 describes the evolutionary procedure. The evaluation process of a genome i.e. evaluate G (t), is a combination of two steps. The first step filters out non standard dance combination generated through crossover operation. Secondly, the fitness of the genome is determined. The intuitive distance measure is used to decide the fitness of the genome. We explain the fitness function in detail in the next subsection.

D. Fitness function

Determination of a fitness function is the most critical and important task in the development process of any GA based system and art to SMart is not an exception. 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. By appropriate dance steps we mean that these steps are different than the available traditional repertoire or a routine choice of a choreographer due to his/her liking, habit, etc. We would like to suggest to a choreographer innovative dance steps but also make sure that these dance steps are not weird. Also we do not mimic the entire routine provided by adavus. Thus we wish to generate dance steps that are not too far or too close (identical) to the adavus. In short the proposed fitness function will be based on distance from adavus. Hence we propose a fitness function that 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 presented below-

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.

Using the notations described to represent dance, we define the above two parameters as follows-

We can say that any p^{th} limb of two dance vectors D_i and D_j are distinct if there exists a single attribute of these two limbs that have different values from each other.

$D_i.L_p \neq D_j.L_p$, if $\exists k$ such that $D_i.L_p.a_k \neq D_j.L_p.a_k$
LVC(D_i, D_j) can be obtained by incrementing LVC by 1 for all distinct limbs, of the two dance vectors.
$\forall p$, if $D_i.L_p \neq D_j.L_p$ then $LVC = LVC + 1$, where p runs from 1 to 6 corresponding to all the limbs.

Furthermore, AVD can be defined as,

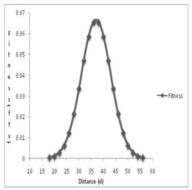

Figure 3. Proposed fitness function

$$\text{AVD}(D_i, D_j) = \sum_{k=1}^{30} |D_i.a_k - D_j.a_k|$$

The following example illustrates in Table II the calculations of LVC and AVD for two dance vectors. The first dance vector (D_1) corresponds to an ideal adavu dance step and the other (D_2) is a randomly generated dance vector.

Absolute Vector Difference (AVD) = 36 & Limb Variation Count (LVC) = 5

Once the values of AVD and LVC are determined distance of dance vectors from ideal dance vectors can be obtained. The distance 'd' is a function of AVD and LVC.

d = f(AVD,LVC) = (0.75AVD)+ (0.25LVC)

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. However we shall experiment in future by varying the weights associated with these parameters.

The fitness function is a function of distance (d) and must be designed carefully. We wish to assign higher fitness value to those dance vectors that are not too close or not too far from the ideal dance vectors. Fig. 3 depicts the expected behavior of our proposed fitness function. We can see that the bell shaped curve in Fig. 3 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.

Fitness function value for the above mentioned dance vector D_2 is.

ffv=ND[(0.75× 36)+(0.25×5]=28.25

The results discussed in the next section ensure that the fitness function lets appropriate dance steps move forward to next generations.

IV. Results and discussions

Generating appropriate dance steps was a challenging task. We faced following two main challenges-

- To avoid impracticable (not doable) as well as impractical (not practiced) dance steps, and
- To generate steps that had surprise value or novelty.

The steps that were identical to Adavus obviously would not be appreciated and the steps that were doable but far from Adavus would not be presentable. We overcame the first challenge by filtering out impractical and impracticable steps by maintaining a database of infeasible dance steps. The details of the infeasible dance step database are given below. Furthermore, by developing an explicit fitness function that was based on the distance of generated steps from the Adavus we overcame the second challenge.

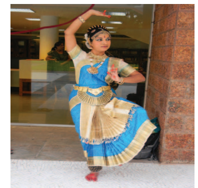

Figure 4. Representation of one of the generated dance mudra.

Figure 5. Representation of one of the generated dance mudra.

The infeasible dance step database maintains dance steps that belong to following categories.

A)Impracticable dance steps: Dance steps that cannot be performed because of the physical constraints are identified and maintained in this database. For example, both feet on heels or feet on toes are impossible in BN. (Ballet allows the dancer to get on toes)

Lifting one leg up is possible when the other is in normal position or half bend which is a characteristic of BN and not possible with other foot in heel or toe position as per BN norms.

B)Impractical dance steps: Keeping both hands at the back are possible but for BN dance it's not aesthetically pleasing to the eyes. Certain hand mudras are impractical in the entire axis while for others it is doable. Hence such types of dance mudras are also excluded.

Besides the above two categories, we noticed that lack of intelligence in the system had to be also explicitly mentioned so that we do not get infeasible combinations. For example, if head is in straight position looking at the audience, it does not have orientation included in it; turning right or left and vice versa. We have identified such positions and we are in a continuous process of evolving this database as and when it occurs.

The Art to SMart system generated some unique results and we requested an expert of BN dance to pose accordingly. Fig. 4 and Fig. 5 shows the generated dance steps[2].

The art to SMart system has generated satisfactory results even after the first generation. It has shown some unique steps that can be performed by a dancer which are very different from the adavus but not totally identical to them. A choreographer can use these steps and use her

[2]Our thanks to Ms. Sapna Naik, BharatNatyam Lecturer, Goa.

Table II
EXAMPLE OF AVD AND LVC CALCULATION

LVC	0+1+1+1+1+1	5
D_1	{1,1} {1,4,0,0,0,-1,0,0} {1,4,0,0,0,1,0,0} {0,0} {-1,0,1,0,0} {0,2,0,0,0}	
D_2	{1,1} {0,4,4,-1,0,0,-1,-1} {0,-1,4,4,0,0,-1,-1} {-2,0} {-1,0,-1,1,-2} {0,2,-1,0,2}	
AVD	0+0+1+0+4+1+0+1+1+1+1+5+4+4+0+1+1+1+2+0+0+0+2+1+2+0+0+1+0+2	36

own creativity also so that she can get totally new and unique poses for a single beat or also use these steps as a building block while generating the whole dance sequence.

In order to obtain feedback we showed results of our system to BN dance performers. We have developed a questionnaire for dance experts' opinion for results generated by our art to SMart system. We have asked them to rank the generated dance mudras on a scale of 1 to 5 as follows: 1- Not Acceptable 2- Bad 3- Ok 4- Good 5- Excellent.

An opinion by most of our dance experts has been that the results are good enough to evoke the creativity process for unique choreographic sequences. The poses shown now by the system for a single beat are unique and can help a teacher to also teach her students new sequences or help in teaching them the choreographic process by asking them to do so. Although our system is currently showing single beat choreography but later for multibeat sequences we can expect similarly good results.

V. CONCLUSIONS

In this paper, we show that art (dance) can be modelled using computational program. It shows that we can successfully use GA based approach to generate novel dance steps that would help a choreographer to demonstrate better creativity.

We proposed a computational model to represent a dance step in the form of a dance vector. We modelled most of the ideal dance steps (Adavus) and enumerated a list of randomly generated dance vectors. GA is used to obtain the list of dance vectors having highest fitness function. The fitness function is explicitly designed to determine dance steps that are not too close (identical) or not too far (weird) from the Adavus.

This system generated output can be used as a suggestion or a tool by the choreographer so that she can use it to her advantage instead of taking the exact replica generated by the system. The hand, leg or even the unique head positions suggested by the system will allow more room for unique choreography and creativity.

Future task includes use of Allaripu and Jatiswaram too for ideal dance steps and defining the measure of a good movement to generate choreography for a multi beat sequence.

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