Revealing the Characteristics of Balinese Dance Maestros by Analyzing Silhouette Sequence Patterns Using Bag of Visual Movement with HoG and SIFT Features

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Abstract. The aim of this research was to reveal and explore the characteristics of Balinese dance maestros by analyzing silhouette sequence patterns of Balinese dance movements. A method and complete scheme for the extraction and construction of silhouette features of Balinese dance movements are proposed to enable performing quantitative analysis of Balinese dance movement patterns. Two different feature extraction methods, namely the Histogram of Gradient (HoG) feature and the Scale Invariant Features Transform (SIFT) descriptor, were used to build the final feature, called the Bag of Visual Movement (BoVM) feature. This research also makes a technical contribution with the proposal of quantifying measures to analyze the movement patterns of Balinese dances and to create the profile and characteristics of dance maestros/creators. Eight Balinese dances from three different Balinese dance maestros were analyzed in this work. Based on the experimental results, the proposed method was able to visually detect and extract patterns from silhouette sequences of Balinese dance movements. Quantitatively, the pattern measures for profiling of Balinese dances and maestros revealed a number of significant characteristics of different dances and different maestros.

Keywords: *Balinese dance; feature; movement; pattern; sequence.*

1 Introduction

Balinese dance is an artistic and cultural asset of the Balinese people that is very well known throughout the world. Apart from being part of the nation's ancestral heritage, including all its religious aspects and cultural values, Balinese dance is one of the main attractions for domestic and foreign tourists. As Balinese dance is still evolving, new dances are developed by young dance experts in several art institutions and colleges. However, dances developed earlier by well-known dance maestros remain and are the 'main act' in every art performance for tourists.

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Passing the baton to the next generation of Balinese dance creators is a good initiative that needs to be sustained. Today, young dancers and Balinese dance creators are striving to master the Balinese dance movements created previously by Balinese dance maestros. The main principles of Balinese dance movements are stored implicitly and explicitly in the storylines and Balinese dance movements. Every Balinese dance maestro has unique characteristics in each of his or her creations. It is therefore very important for dancers and dance creators to know and explore the characteristic values of the maestros who created the dances. This will facilitate and enable a deeper understanding of the meaning and choreography of new Balinese dance movements and prevent the degradation of Balinese dance standards that are rooted in the past.

This study aimed to explore and identify patterns of Balinese dance movements created by several Balinese dance maestros explicitly and quantitatively. Technically, this study analyzed the differences in the characteristics of the Balinese dance maestros by extracting dance movement patterns from some of their dances. Previous studies on capturing and modeling Indonesian traditional dances have been conducted by Zaman, *et al.* [1] and Hegarini, *et al*. [2]. Hegarini, *et al.* [2] documented and stored several Indonesian traditional dances digitally using motion capture from animation-making technology. Zaman, *et al.* [1] not only captured dance movements using motion capture but also modeled the dance movements using generative long short-term memory network. The fundamental difference with our research is that the dance movement models that were built in the two previous studies were based on raw data from motion capture technology, whereas our method extracts and builds a dance movement model by utilizing raw features in video images. This provides a broader opportunity to analyze patterns in existing dance videos, without having to carry out the recording and re-transformation process with additional tools and technology.

The main contribution of this research is the proposed method as well as a complete scheme for the extraction and construction of silhouette features of Balinese dance movements to enable quantitative analysis of Balinese dance movement patterns. Figure 1 shows the general scheme of our proposed method. Two different feature extraction methods, namely the Histogram of Gradient (HoG) feature and the Scale Invariant Features Transform (SIFT) descriptor, were used to build the final feature called Bag of Visual Movement (BoVM). In addition, this research also makes a technical contribution by proposing quantitative measures for the analysis of Balinese dance movement patterns to facilitate building the profiles and characteristics of Balinese dances as well as the profiles and characteristics of Balinese dance maestros/creators. Apart from the technical contribution, this research also contributes to the preservation of the highly artistic cultural values of this national heritage by adopting computer vision technology, which is rapidly developing today.

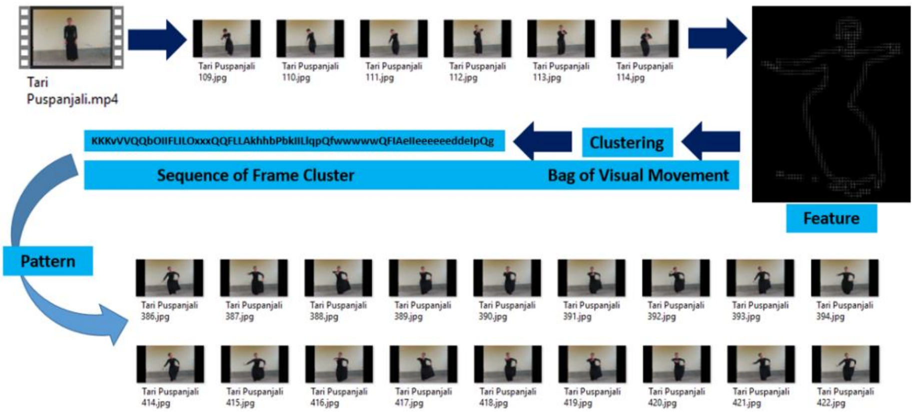

Figure 1 General scheme of the proposed method for the extraction of features and bag of visual movement.

The next section in this paper, Section 2, will describe the COMPUDANCE project, which provided the main framework for this research. The proposed method is described in detail in Section 3. The experimental results are presented in Section 4 along with some analyses. Section 5 summarizes the conclusions of this study and provides an overview of future research plans.

2 Project COMPUDANCE

The COMPUDANCE (Computerization of Dances) project is one of the research projects initiated by the Virtual, Vision, Image and Pattern Research Group (VVIP-RG) [3]. One of the technical objectives of this project is to extract and quantitatively analyze visual patterns contained in Balinese dance movements created by Balinese dance maestros. In this paper, the first study of the COMPUDANCE project is presented, which aimed to explore and reveal the characteristics of Balinese dance maestros by analyzing silhouette sequence patterns of Balinese dance movements. The final objective of COMPUDANCE is to build a complete modeling and machine learning system capable of creating Balinese dances automatically based on the characteristics of Balinese dance maestros. The study of the different characteristics of Balinese dance maestros and their creations will be the basis for further research efforts in designing a method for creating Balinese dances automatically using a computer with reference to the characteristics of Balinese dance maestros.

The first research step of the COMPUDANCE project was to build a dataset of video recordings of Balinese dance movements that can be used for research in the field of computer vision, especially related to the problem of pattern recognition in video. At this early stage, COMPUDANCE has captured and documented a dataset of Balinese dance videos containing eight Balinese dances. All eight Balinese dances in this dataset are female Balinese dances, created by three different Balinese dance maestros.

The titles of the Balinese dances and their creators can be found in Table 1. In this video dataset, each dance was performed by a female Balinese dancer. The dancer wore a black costume with minimal accessories. The video was taken against a bright background contrasting with the dark color of the dancer's costume (Figure 2). This was done to facilitate the next step of the research, namely extracting the silhouette information from Balinese dance movements for patterns analysis. The Balinese dance videos resulting from this recording process did not go through any further editing processes.

Table 1 Dataset of balinese dances and maestros.

Title	Creator/maestro
Puspanjali	N.L.N. Swasthi Wijaya Bandem (N.L.N. Suasthi Widjaja)
Sekar Jagat	N.L.N. Swasthi Wijaya Bandem (N.L.N. Suasthi Widjaja)
Cendrawasih	N.L.N. Swasthi Wijaya Bandem (N.L.N. Suasthi Widjaja)
Wiranjaya	I Ketut Merdana
Nelayan	I Ketut Merdana
Margapati	I Nyoman Kaler
Wiranata	I Nyoman Kaler
Panji Semirang	I Nyoman Kaler

Figure 2 Examples of four Balinese dance videos from the dataset of the COMPUDANCE project.

3 Proposed Methods

To explore the characteristics of the Balinese dance maestros, several Balinese dances created by each maestro were analyzed in groups. Analysis of the silhouette sequence patterns of Balinese dances was carried out by using two different feature extraction methods, namely the HoG feature and the SIFT descriptor (Figure 3). This was done to ensure the validity and robustness of the Bag of Visual Movement (BoVM) model that was built later. BoVM is expected to provide fairly stable pattern information, even though it is built with a different feature extraction method. This BoVM model is the final feature that serves as the input for the sequence pattern analysis engine with a suffix tree structure.

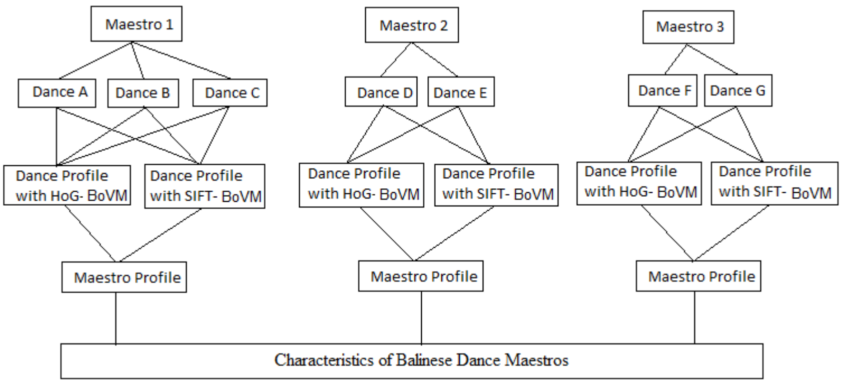

Figure 3 General scheme for building the characteristics of Balinese dance maestros.

In the following subsections, the feature extraction method used to build BoVM will be described. Before feature extraction was carried out, each Balinese dance video in the COMPUDANCE dataset was extracted into 500 image frames (Figure 4). Each image frame was resized to a size of 352 x 640 pixels (Figure 5). After the feature extraction process had been carried out, the final BoVM feature construction scheme was carried out. Through the final BoVM feature, a Balinese dance video is represented in the form of a coded sequence so that the patterns can be analyzed using a suffix tree structure.

Figure 4 Extraction of image frames from Balinese dance videos.

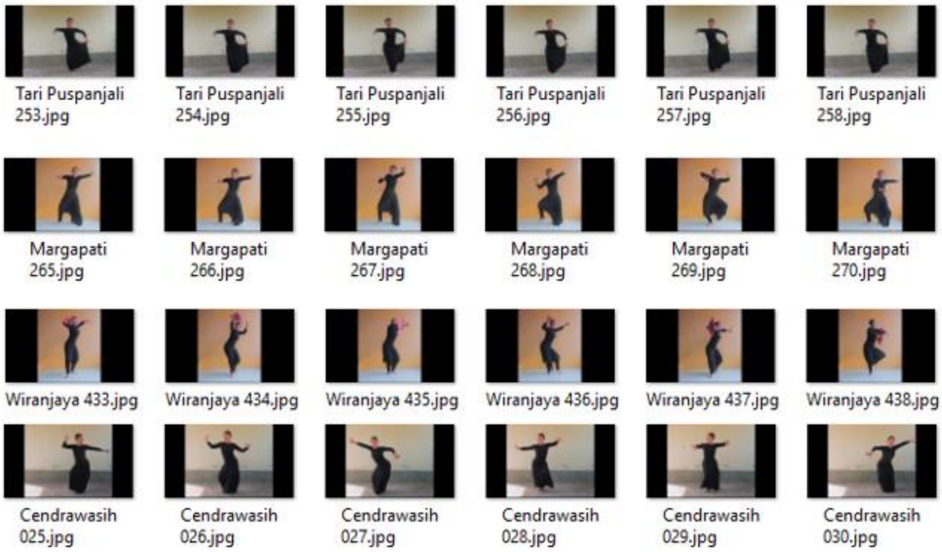

Figure 5 Examples of image frames extracted from four different Balinese dance videos.

3.1 Histogram of Gradient (HoG)

HoG is a gradient-based feature [4,5]. HoG is very powerful in representing features such as the edges and curves of an object in the image. The HoG feature contains not only information about the magnitude of the gradient at an image point, but also information on the direction of the gradient vector. This characteristic provides the basis for the initial decision to use the HoG feature in providing information on the silhouette shape of each movement extracted from the images frames of the Balinese dance videos.

In this study, the HoG feature was applied to the binary image obtained by the Otsu binarization method [6] from each image frame of the Balinese dance videos (Figure 6). To build the HoG feature, first the gradient values and gradient directions at each point in the image frame were calculated. The gradient image was then divided into several smaller image areas. In each of these small areas, a gradient histogram was constructed by grouping gradient points into groups of gradient directions. Gradient direction groups were formed by evenly dividing the range of the gradient directions from 0 to 180 or 360 degrees. The histogram of each small area was then normalized by taking into account the larger overlapping area. The final HoG feature was obtained by concatenating all the histogram vectors from each of the normalized areas.

In our experiments, we used the HoG feature from VLFeat [14]. For the HoG feature extraction parameters, we used 4 pixels as cell size with 4 different orientations (Figure 6). With these parameters, we obtained a dimension of 14,080 vectors for the HoG feature in 16 different HoG layers for each image frame. Thus, for one video with 500 image frames we had 8,000 HoG feature layers in total.

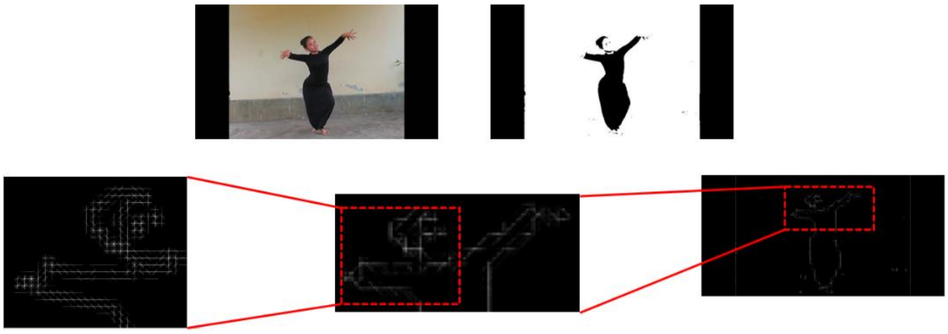

Figure 6 Example of one image frame, the binary image, and the HoG feature image.

3.2 Scale Invariant Features Transform (SIFT) Descriptor

Based on a number of surveys, an image feature that is widely used to process the matching task in image retrieval and indexing systems is the Scale Invariant Features Transform (SIFT) [7-13].

In our experiments, we implemented the Dense SIFT feature from VLFeat [14]. The SIFT feature was applied to the binary image obtained by the Otsu binarization method [6] from each image frame of the Balinese dance videos. We then densely calculated the SIFT descriptors of every 5 pixels using a square region of 50 pixels. Each descriptor contained 128 feature values. With these parameters, we had a dimension of 4,018 vectors for each SIFT descriptor in 128 different SIFT feature layers for each image frame. However, only the first 20 SIFT feature layers were used. Thus, for one video with 500 image frames, we had 10,000 SIFT feature layers in total.

3.3 Bag of Visual Movement (BoVM)

The construction of the proposed BoVM feature was inspired by the concept of Bag of Visual Words [8,9] from word spotting research. Figure 7 shows the construction scheme of the BoVM feature. After the HoG and SIFT feature extraction process we apply two steps of K-means clustering. The first step of K-means clustering (with K = 100) clusters the HoG features from all 8,000 HoG feature layers or the SIFT features from all 10,000 SIFT feature layers. From this first clustering process we assign a cluster code to each HoG or SIFT feature layer in each image frame. For each image frame we then build a joint histogram of cluster codes from all HoG or SIFT feature layers that belong to that image frame. After this step one image frame has one histogram with layer cluster codes as a Bag of Visual Movement (BoVM).

With the BoVM feature from each image frame we then apply the second step of K-means clustering (K = 50) to cluster those 500 BoVM features. Figure 8 shows some examples of different image frame clusters resulted from the BoVM clustering process. This clustering process assigns a cluster code to all 500 image frames and generates the sequence of frame cluster codes from one video (Figure 9). This sequence of 500 BoVM cluster codes will be sent to the pattern analysis module with a suffix tree structure.

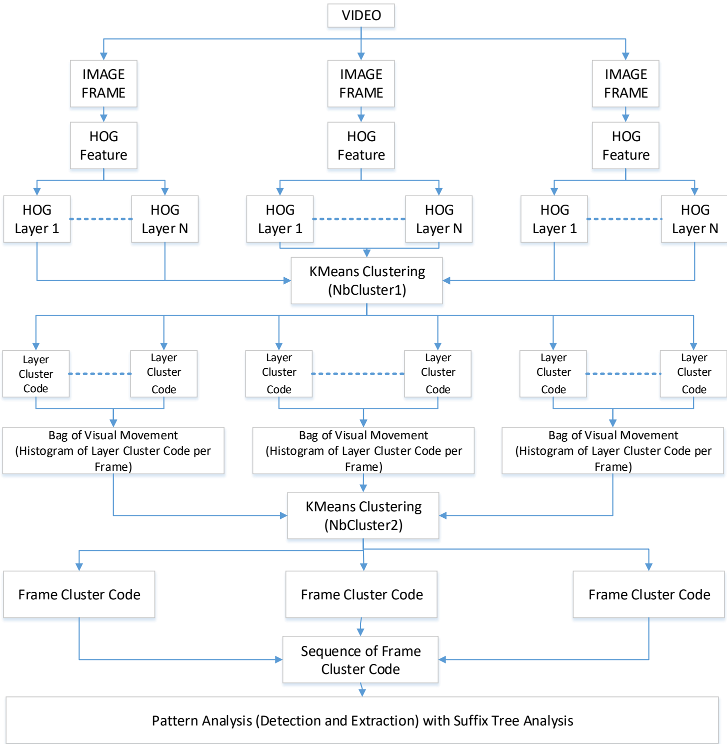

Figure 7 Construction scheme of the BoVM feature from the HoG feature. The same scheme is used to construct the BoVM feature from the SIFT feature.

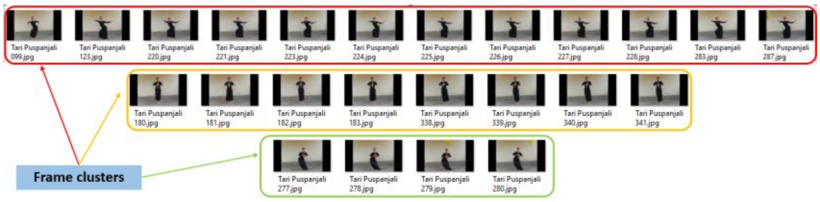

Figure 8 Examples of different image frame clusters resulted from the BoVM clustering process.

Figure 9 Sequence of BoVM cluster codes from one Balinese dance video.

3.4 Suffix Tree Analysis

To analyze the silhouette sequence patterns that are already represented in the sequence of 500 codes, we generate and use a suffix tree [15] (Figure 10). The suffix tree of a string (sequence of character code) is a tree that contains all paths to build all suffix trees of that string. The suffix tree detects and localizes patterns in a string, for example sub string repetitions and the longest common sub string.

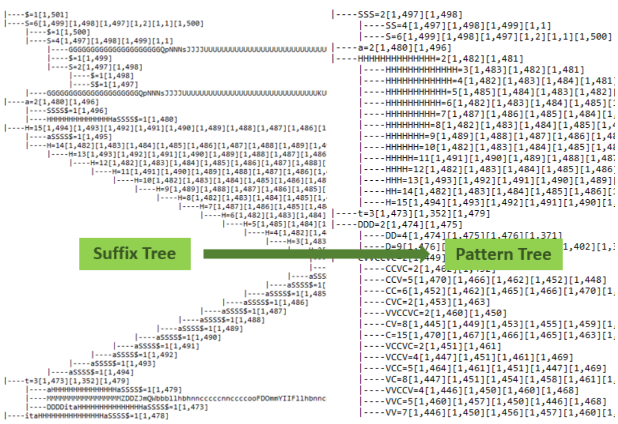

Figure 10 Example of suffix tree generated and pattern tree detected from the sequence of BoVM cluster codes.

4 Results and Discussion

To analyze the patterns detected by the proposed method, we first identified patterns in Balinese dance movement silhouette sequences and then defined 13 quantitative pattern measures to create pattern profiles of Balinese dances.

4.1 Pattern Definition and Pattern Measures

A detected pattern is a sequence of code (from an image frame) that appears at least twice (in two different frame positions). In our experiment, we detected only patterns with a minimum length of 5 (five) image frames. Our proposed method with HoG feature extraction and Bag of Visual Movement is robust in detecting patterns. To analyze and measure the silhouette sequence patterns quantitatively, we propose 13 pattern measures to build the pattern profile of Balinese dances (Table 2).

Table 2 Pattern measures for pattern profiles of Balinese dances.

Measure	Unit
Total Number of Patterns	pattern
Average Number of Patterns per Feature Layer	pattern
Max Pattern Length	frame
Average Pattern Length	frame
Max Frequency of Patterns per Feature Layer	time
Average Frequency of Patterns per Feature Layer	time
Min Percentage of Pattern Coverage per Feature Layer	%
Max Percentage of Pattern Coverage per Feature Layer	%
Average Percentage of Pattern Coverage per Feature Layer	%
Number of Distance Pattern Entities	-
Min Pattern Distance	frame
Max Pattern Distance	frame
Average Pattern Distance	frame

4.2 Experimental Results

Prior to analyzing and measuring the patterns quantitatively, we visually analyze the detected silhouette sequence patterns. Figures 11 to 13 show some examples of detected patterns from three different Balinese dances. Table 3-5 show the pattern profiles of all Balinese dances from our dataset. For each dance, the pattern profile was calculated from two different features for BoVM construction, the HoG feature and the SIFT feature. Finally, Table 6 shows the final pattern profiles of the Balinese dance maestros. The pattern profile of each Balinese dance maestro is calculated from the average of each pattern measure value of the pattern profiles from all Balinese dances created by the maestros.

Figure 11 Examples of a pattern detected in the Dance of Puspanjali. This pattern appears in image frame no. 180-184 and image frame no. 338-342.

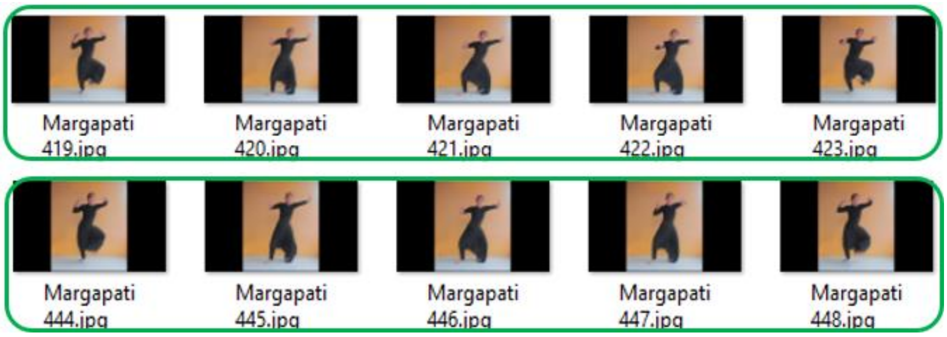

Figure 12 Examples of a pattern detected in the Dance of Margapati. This pattern appears in image frame no. 419-423 and image frame no. 444-448.

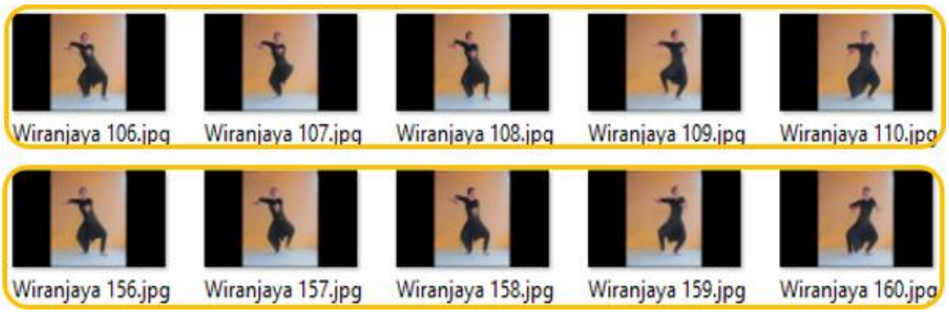

Figure 13 Examples of pattern detected in the Dance of Wiranjaya. This pattern appears in image frame no. 106-110 and image frame no. 156-160.

Table 3 Pattern profile of Balinese dances from N.L.N. Swasthi Wijaya Bandem.

Measure	Unit	Puspan jali	Puspan jali	Sekar Jagat	Sekar Jagat	Cendra wasih	Cendra wasih
		HoG	SIFT	HoG	SIFT	HoG	SIFT
Total Number of Patterns	pattern	154	217	72	86	4	5
Average Number of Patterns per Feature Layer	pattern	9.0588	10.3333	4.2353	4.0952	0.23529	0.2381
Max Pattern Length	frame	15	33	9	11	6	6
Average Pattern Length	frame	6.5844	8.2488	6.125	6.395	5.25	5.4
Max Frequency of Patterns per Feature Layer	time	3	3	3	3	2	2
Average Frequency of Patterns per Feature Layer	time	2.0195	2.0138	2.0417	2.0116	2	2
Min Percentage of Pattern Coverage per Feature Layer	%	11.6	14.6	3.4	0	0	0
Max Percentage of Pattern Coverage per Feature Layer	%	44.8	42.6	15.8	17.8	5.7239	4.0404
Average Percentage of Pattern Coverage per Feature Layer	%	21.5294	28.8381	9.1647	9.4	0.73282	0.8658
Number of Distance Pattern Entities	-	157	220	75	87	4	5
Min Pattern Distance	frame	6	7	5	6	8	8
Max Pattern Distance	frame	383	470	389	301	203	27
Average Pattern Distance	frame	87.7516	97.1045	51.2	54.6322	58	19.8

Table 4 Pattern profile of Balinese dances from I Ketut Merdana.

Measure	Unit	Wiran jaya	Wiran jaya	Nelayan	Nelayan
		HoG	SIFT	HoG	SIFT
Total Number of Patterns	pattern	132	59	83	58
Average Number of Patterns per Feature Layer	pattern	7.7647	2.8095	4.8824	2.7619
Max Pattern Length	frame	21	13	14	11
Average Pattern Length	frame	7.0227	6.6949	6.3614	6.2414
Max Frequency of Patterns per Feature Layer	time	3	2	2	2
Average Frequency of Patterns per Feature Layer	time	2.0303	2	2	2
Min Percentage of Pattern Coverage per Feature Layer	%	4.2	0	5.2	0
Max Percentage of Pattern Coverage per Feature Layer	%	34	11.2	22.6	15
Average Percentage of Pattern Coverage per Feature Layer	%	17.2471	7.0667	10.4235	6.2952
Number of Distance Pattern Entities	-	136	59	83	58
Min Pattern Distance	frame	6	7	5	6
Max Pattern Distance	frame	367	82	184	160
Average Pattern Distance	frame	81.4926	26.3559	27.8554	30.1897

Table 5 Pattern profile of Balinese dances from I Nyoman Kaler.

Measure	Unit	Marga pati HoG	Marga pati SIFT	Wira nata HoG	Wira nata SIFT	Panji Semirang HoG	Panji Semirang SIFT
Total Number of Pattern	pattern	133	89	75	21	52	28
Average Number of Pattern per Feature Layer	pattern	7.8235	4.2381	4.4118	1	3.0588	1.3333
Max Length of Pattern	frame	15	12	17	7	18	6
Average Length of Pattern	frame	6.3459	6.4045	6.6933	5.5714	6.7115	5.2857
Max Frequency of Pattern per Feature Layer	time	3	2	2	2	3	2
Average Frequency of Pattern per Feature Layer	time	2.0526	2	2	2	2.0192	2
Min Percentage of Pattern Coverage per Feature Layer	%	4	4	0	0	0	0
Max Percentage of Pattern Coverage per Feature Layer	%	36.8	16.8	30.2	6	37.8	7.4
Average Percentage of Pattern Coverage per Feature Layer	%	16.6471	9.1619	8.8235	2.1429	7.3647	2.5905
Number of Distance Pattern Entity	-	140	89	75	21	53	28
Min Distance of Pattern	frame	4	6	5	6	5	7
Max Distance of Pattern	frame	434	264	462	305	340	203
Average Distance of Pattern	frame	70.1643	27.382	116.4533	64.381	110.0189	18.0714

Table 6 Pattern profile of Balinese dance Maestros.

Measure	Unit	Swasthi	Merdana	Kaler
Total Number of Patterns	pattern	89.666667	83	66.333333
Average Number of Patterns per Feature Layer	pattern	5.591578	4.554625	3.64425
Max Pattern Length	frame	13.333333	14.75	12.5
Average Pattern Length	frame	6.3339167	6.5801	6.1687167
Max Frequency of Patterns per Feature Layer	time	2.6666667	2.25	2.3333333
Average Frequency of Patterns per Feature Layer	time	2.0144333	2.007575	2.0119667
Min Percentage of Pattern Coverage per Feature Layer	%	4.9333333	2.35	1.3333333
Max Percentage of Pattern Coverage per Feature Layer	%	21.79405	20.7	22.5
Average Percentage of Pattern Coverage per Feature Layer	%	11.755137	10.258125	7.7884333
Number of Distance Pattern Entities	-	91.333333	84	67.666667
Min Pattern Distance	frame	6.6666667	6	5.5
Max Pattern Distance	frame	295.5	198.25	334.66667
Average Pattern Distance	frame	61.414717	41.4734	67.74515

4.3 Discussion

From three Balinese dances created by N.L.N. Swasthi Wijaya Bandem, the dance *Cendrawasih* had the smallest number of patterns, while *Puspanjali* had the highest number of patterns. From the two Balinese dances created by I Ketut Merdana, the dance *Wiranjaya* showed more patterns compared to *Nelayan*. From the three Balinese dances created by I Nyoman Kaler, the dance of *Margapati* had the highest number of patterns, while *Wiranata* and *Panji Semirang* had almost the same number of patterns. Dances with a smaller number of patterns have more varied movements than dances with more patterns. For example, it was found that there were fewer repeated movements in *Cendrawasih* compared to *Puspanjali*, *Wiranjaya* and *Margapati*. This is also reflected in the values of the Average Number of Patterns per Feature Layer and the values of Average Percentage of Pattern Coverage per Feature Layer. By analyzing the pattern profile of each Balinese maestro, we found that N.L.N. Swasthi Wijaya Bandem had the highest average number of patterns, while I Nyoman Kaler had the lowest average number of patterns. This means that I Nyoman Kaler generally creates more varied movements in his dances.

N.L.N. Swasthi Wijaya Bandem reflects a more female type of dance in her creations by using more repetitive movements. However, both maestros showed a wide range of pattern variation in their creations, from Balinese dances with a low number of variations (more patterns) to Balinese dances with a high number of variations (fewer patterns), while I Ketut Merdana showed a more or less equal number of pattern variations in each of his creations. Based on the values of Average Length of Pattern, all Balinese dance maestros in this dataset had an average pattern length of 6 frames. In general, for all Balinese dance maestros in this dataset, the value of Max Frequency of Patterns per Feature Layer was only 2 times.

5 Conclusion and Future Works

The COMPUDANCE project has built an initial video recording dataset of Balinese dance movements. The present study made a technical contribution by proposing quantitative measures for analyzing Balinese dance movement patterns to be able to build profiles and characteristics of Balinese dances as well as profiles and characteristics of Balinese dance maestros/creators. The analysis of the movement silhouette patterns in Balinese dances was carried out using two different feature extraction methods, namely the HoG feature and the SIFT descriptor. The final BoVM feature is constructed by two K-means clustering processes. Based on the experimental results, the proposed method was able to visually detect and extract patterns of silhouette sequences from Balinese dance movements.

Quantitatively, the pattern measures for pattern profiles of Balinese dances and maestros showed some significant characteristics of the different dances and the different maestros. It was found that there were fewer repeated movements in the dance *Cendrawasih* compared to *Puspanjali*, *Wiranjaya* and *Margapati*. I Nyoman Kaler generally creates more varied movements in his dances. N.L.N. Swasthi Wijaya Bandem reflects a more female type of dance in her creations by using more repeated movements, while I Ketut Merdana shows a more or less equal number of pattern variations in each of his creations. For future works, this initial study of the different characteristics of Balinese dance maestros and their creations will be used as the basis for designing the process of creating Balinese dances automatically.

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