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HMM Causal Topology Design for View Independent Posture Recognition

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Abstract: **A posture is a form of non-verbal communication associated with part of the body which is rich in way for individuals to express a variety of desire, feelings and thoughts. It is a challenging task to recognize human posture via computer as it involved various kind of issues ranging from image, recognition algorithm and system resources. We proposed to solve viewpoint variation issue through causal topology design of Hidden Markov Model (HMM) for supporting view independent posture recognition. This causal topology design utilized causality to perceive an event with a determined set of cameras that allows flexibility for end-user to locate at anywhere. Characteristic view determination approach is applied to deduce the minimal set of viewpoint required representing a posture, and dynamic topology estimation method is used to result a causal HMM. The recognition result of the causal HMM demonstrated a comparable recognition accuracy for the given test data and a significant improvement in reducing the supervised training data to represent a posture.**

Keywords: Hidden Markov Model (HMM), causal topology design, characteristic view, dynamic topology estimation, view independent, posture recognition

I. Introduction

Vision-based recognition and understanding of human actions have been studied extensively and remain as an active research area of computer vision in recent years. Human action recognition always compromises with multiple issues such as cost, view dependent, ambiguity, extendibility, processing power and robustness. There are many approaches devised to enable the machine to understand human action and to perform the reaction autonomously. Artificial intelligence, stochastic model and statistical techniques are widely used among the researchers.

This research emphasized on the posture recognition. There are several techniques for posture recognition given the feature extracted dubbed template-matching, dictionary lookup, statistical matching, linguistic matching, neural network, and ad hoc methods [1]. Some of the methods are suitable for only one type of feature representation, while others are more generally applicable.

This research focuses on the view dependency issue where it suggested a solution for view independent posture recognition using causal topology design in Hidden Markov Model (HMM) for multiple silhouettes images. HMM is used as the recognition engine due to its proven capability in coping with the stochastic properties in posture recognition. The HMM is a powerful statistical tool for modeling generative sequences that can be characterized by an underlying process generating an observable sequence. The model is explainable, extensible and adaptable to integrate with other theory or concept in implementation to achieve "higher order" of HMM. Generally, the motivation for this research is originated from the fact that human have natural behaviors that act with a purpose in consciously or unconsciously; and human visual perception performs recognition action amazingly accurate even though there is vague information.

The research assimilated the causal topology design in the HMM to exhibit the viewpoint invariant ability of human through an optimum set of input cameras. The view independent capability enables the human object locates without constraint in a closed environment; and the system is able to recognize the posture without any major issue. To achieve view independent, the characteristic view determination [2] is applied to deduce a minimal set of viewpoint required on the human object in representing a posture; and the dynamic topology estimation method [3] is used to result a causal HMM topology design. The characteristic view required view grouping via aspect-graph. The aspect-graph is a graph where each of the nodes is a prototypical representing one or more neighboring grouped views. In order to recognize 3D objects from 2D images, the aspects are formed using a notion of shape similarity between views. Here, the shock-based matching is used to find the similarity between the shape views. Shock-based matching possesses greater capability to represent a larger aspect with a single prototype if compared with curve matching. It used shock graph which is an emerging shape representation for object recognition, where a 2-D silhouette is decomposed into a set of qualitative parts, captured in a directed acyclic graph.

As a series of characteristic-view-determined silhouettes images are undergone feature extraction, classification and codeword construction, the HMM then starts to develop a topology based on a likelihood criterion and a heuristic evaluation of complexity that best represent the dynamic structure of the data. The algorithm used is iterative pruning. It yields a simplified HMM topology to capture the statistical behavior of the data with minimal set of state transitions. Such topology truly reflects the causal relationship among the states that enable the representing posture been recognized. Theoretically, via causal estimation, the state representation (from camera viewpoint) and transition are reduced and the supervised training dataset for the HMM on each defined posture is mitigated. The decrease in the number of camera input for the HMM leads to the requirement in identifying few critical important camera position that sufficiently capture human posture regardless of the human object's orientation and position in an environment. This research showed the causal HMM is able to recognize the given unknown posture as accurate as complete/ergodic HMM topology with the advantage of location independent for the human object within predefined closed area.

II. Literature Review

Posture recognition enables humans to interface with the machine and interact naturally without any mechanical devices. It can be conducted with techniques from computer vision and image processing. Various algorithmic techniques have been introduced and used over the years for the posture and gesture recognition. These techniques can be classified into three major categories called feature extraction and statistical models, learning algorithms and miscellaneous algorithms [4]. The feature extraction and statistical models such as principle component analysis (PCA), active shape models, template-based, cause analysis and fuzzy logic deal with the feature extraction in the form of mathematical quantities from data captured through sensors or images. The learning algorithm refers to the machine learning algorithms that deal with the learning of the posture based on the data manipulation and weight assignment. Neural networks, HMM and instance-based learning are the examples. The miscellaneous algorithm refers to others combinatory techniques such as linguistic approach, appearance-based model and distributed model.

HMM is a sophisticated statistical method for human posture training, modeling and matching to recognize the human motion. HMMs have been used prominently and successfully in speech and posture recognition. It was introduced in the mid 1990's, and quickly became the recognition method of choice, due to its implicit solution to the segmentation problem. Here, the HMM is designed to integrate with other methodologies to yield hybrid HMM dubbed causal HMM to cope viewpoint limitation. Three components that contributed to this initiative are feature extraction, HMM and causal.

A. Feature Extraction

Feature extraction is an essential image pre-processing step to pattern recognition and machine learning problems. It is often decomposed into feature construction and feature selection. Gradient-based and star skeleton shape descriptors are the methods that can apply on silhouette image to extract posture's pixel boundary and shape.

Gradient-based shape descriptor that could be applied to both binary and grayscale images, extract gradient features along the object boundaries to obtain gradient information at different orientations and scales, and then aggregate the gradients into a shape signature [4]. The signature derived from the rotated object is circularly shifted version of the signature derived from the original object. This property is known as circular-shifting rule. The shape descriptor is defined as the Fourier transform of the signature. There are various approaches to measure distance for the descriptor by taking the circular-shifting rule into account such as centroid distance, curve bending angles and boundary curvature. In order to capture the shape information, the process extracts local image gradient on the boundary while tracing it. The gradient feature is a two-dimensional vector which may have various orientation and magnitude depending on the local intensity distribution. For the gradient point-to-centroid and gradient point-to-point, the image's centroid is identified and be partitioned into several region for boundary identification process. In gradient point-to-centroid, the computation involves the distance of each boundary pixel to the centroid in the region; while the gradient point-to-point is the measurement of curve bending angles, direction and magnitude of each boundary pixel to its neighborhood.

On the other hand, star skeleton is a kind of representative features to describe a human posture skeletonization [6]. It is defined as joining gross extremities of boundary to its centroid. The features consist of the several vectors which are the distance from the extremities of human contour to its centroid. The basis of the star skeleton is to connect the extremities of human contour with its centroid. To find the extremities, each distance from boundary point to the centroid is calculated through boundary tracking in a clockwise or counter-clockwise order. In distance function, the extremities are located at local maxima. Noise reduction should be applied to the distance function by using a smoothing filter or low pass filter. Consequently, the final extremities are detected by finding local maxima in smoothed distance function.

B. Hidden Markov Model (HMM)

A Hidden Markov Model (HMM) is a statistical model in which the system being modeled is assumed to be a Markov process with unobserved state [7]. A HMM can be considered as the simplest dynamic Bayesian network. In HMM, the state is not directly visible, but output dependent on the state is visible. In fact, a HMM is a collection of finite states connected by transitions. Each state is characterized by two sets of probabilities - a transition probability and either a discrete output probability distribution or continuous output probability density function, which given the state that defines the condition probability of emitting each output symbol from a finite alphabet or a continuous random vector. There are four types of HMM algorithms namely forward, backward, Viterbi and Baum-Welch algorithm used to solve different aspect of the HMM issues with the given parameters, state sequence and input training data.

The theory of HMM was developed and applied in speech recognition in the late 1960's and early 1970's [8]. Later, HMMs are employed to represent the postures, which are represented in sequential symbols, with their parameters are learned from the training data. Based on "the most likely performance" criterion, the postures can be recognized through evaluating the trained HMMs. The HMM can be used in solving three basic canonical problems dubbed evaluation problem, decoding problem and learning problem [9]. In the evaluation problem, it scores the match between a model and an observation sequence, which could be used for isolated posture recognition. In the decoding problem it can find the best state sequence given an observation sequence, which could be used for continuous posture recognition. In the learning problem, it provides model parameters in such a way that the model possesses a high probability of generating the observation for a given model and a set of observations. Therefore, the learning process is referred as establishing posture models according to the training data.

C. Causality

Causality is referred as a relationship between one event or action that precedes and initiates a second action or influences the direction, nature or force of a second action [10]. In scientific study, causality must be observable, predictable and reproducible. Whenever there is causal relationship exist, there must be a causal chain which is an ordered sequence of events in which any one event in the chain causes the next. There are three types of causes dubbed necessary causes, sufficient causes and contributory causes.

In posture recognition area, causal knowledge is still yet fully applies widely. This is due to the difficulty in recognizing the causal pattern which yields unclear implementation and the doubt in running real time. However, the causal concept doesn't standalone as one implementation; it serves as an enhancement to integrate with existing models or techniques to spur up the performance. For example, [11] initiated an automatic segmentation of echocardiographic images using full causal Hidden Markov Model (FCHMM). For this research, the causal topology design is implied on the silhouettes image's sequential symbol inputs to decide the pattern and structure so that it is best representing a defined posture through minimum amount of image taken by calibrated cameras from different angle viewing point prior sending to HMM for training. Subsequently, the HMM can train less and constructs a sound causal transition state model that is able to perform recognition as effective as full topology HMM.

III. RESEARCH METHODOLOGY

The posture identification via vision-based input devices like camera is the prerequisite process in this research. The posture representation and description refer to the input image being converted to silhouettes image. Multiple silhouettes representation is simple, view invariant, and capable to resolve the ambiguity in recognition caused by self-occlusion. In multiple silhouettes representation of human posture, feature extraction is applied to each silhouette images. In general, the base of image acquisition, preprocessing, description and recognition processes are referred to the work from [12] [14] in which gradient-based shape descriptor point-to-centroid is applied on the synthetic model's silhouettes images to extract contour point and center point. The contour points are calculated based on 12 bins template. Then, K-means clustering is adapted for the classification of feature set obtained. The K-means algorithm takes the input parameter, k, and partitions a set of n objects into k clusters so that the resulting intra-cluster similarity is high but the inter-cluster similarity is low. Cluster similarity is measured in regard to the mean value of the objects in a cluster, which can be viewed as the cluster's center of gravity. The algorithm attempts to determine k partitions that minimize the squared error function. A symbol which corresponds to a code-word in the code book created by K-means is assigned to each silhouette image. A sequence of code-word is formed by cameras' view and used to create the HMM models.

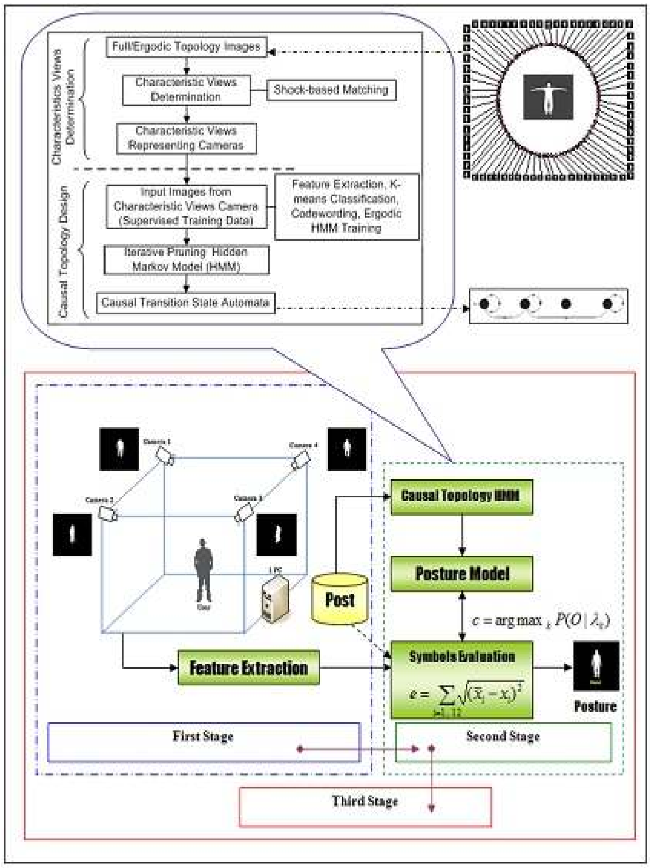

Figure 1. Research Model

Indeed, the causal HMM is generated via the inclusion of characteristics views determination and iterative pruning process. Characteristic views determination, which run before feature extraction, is intended to obtain a representative and adequate grouping of views, such that a given level of recognition accuracy may be achieved using the minimum number of stored views (camera); while the iterative pruning process which execute during model training enables the training data (silhouette images from camera) reveal its own dynamic data structure/ pattern (causal relationship) which yield causal topology design. Figure 1 shows the framework of proposed research model.

A. Characteristic View Determination

Characteristic views (CV) enable user obtains a representative and adequate grouping of views, such that a given level of recognition accuracy may be achieved using the minimum number of stored views [13]. This has important implications for the storage space needed to represent each object, and the number of matches which must be performed at run-time for the purpose of recognition.

View grouping has been addressed using CVs and aspect graphs (AG) which enumerates all possible appearances of an object [2]. This view-based method is recognized 3D objects from 2D images via aspect-graph structure, where the aspects are formed using a notion of shape similarity between views. Specifically, the viewing sphere is endowed with a metric of dissimilarity for each pair of views and the problem of aspect generation is viewed as a "segmentation" of the viewing sphere into homogeneous regions. The goal of view-based approach is to represent a 3D object with a set of 2D views, resulting in a significant reduction in dimensionality by comparing key 2D images rather than comparing 3D objects. Efficiency mandates that the complete set of views, which are redundant to some degree, must be somehow reduced to a minimal set.

1. Consider every view to be an aspect and its own characteristic view. An object with *M* views will initially contain *M* aspects each composed of one view.
2. Compute the distance between each pair of neighboring aspects.
3. Select the pair aspects with the minimal disctance:
   a. If they are within each other group's boundaries, combine the two aspects into a single aspect.
   b. The view with the minimal distance to other views in the new group/aspect becomes the new characteristic view for that aspect.
4. Recompute the distances between the neighboring characteristic views.
5. Repeat step 3 and step 4 with the new aspects as represented by their characteristic views of the formed aspects.
6. The process ends when there are no aspect views that can be grouped without violating the aspect boundaries.

Figure 2. The Aspect-Combination Algorithm used to Merge the Views of an Object into Aspects

Basically, the object shape in image changes as the angle at which it is viewed is changed respectively. The shape generally holds a level of consistency and gradual change until a significant change takes place. The viewing sphere is endowed with a metric *d* indicating "distance" between two views which measures the dissimilarity between the shapes of projected views of the object. Shock matching is used as metric. It is computed by finding the least action path in deforming the shape represented by its shock graph. The CV is generated via aspect-combination process in accordance with the criteria - local monotonicity and object-specific distinctiveness. Figure 2 illustrates the aspect-combination algorithm used to merge the views of an object into aspects. The end result is a set of aspects which representing the characteristic view of the object's posture. Each aspect contained a "representative aspect" which denotes the camera number image needed for feature extraction process.

B. Iterative Pruning Process

The causal topology design is aimed to further abstract and simplify the characteristic views determined HMM topology to yield a "light" HMM for easy and accurate posture recognition process, apart from view independent advantage. Iterative pruning is a method to construct a topology based on a likelihood criterion and a heuristic evaluation of complexity [3]. The algorithm iteratively prunes state transition from a large general HMM topology until a topology is obtained to concisely represent the dynamic structure of the data. Such topology is a simplified version of the causal relationship among the state. The goal of the pruning is to allow the data to reveal its own dynamic structure without external assumptions concerning the number of states or pattern of transition. Figure 3 shows the iterative pruning algorithm.

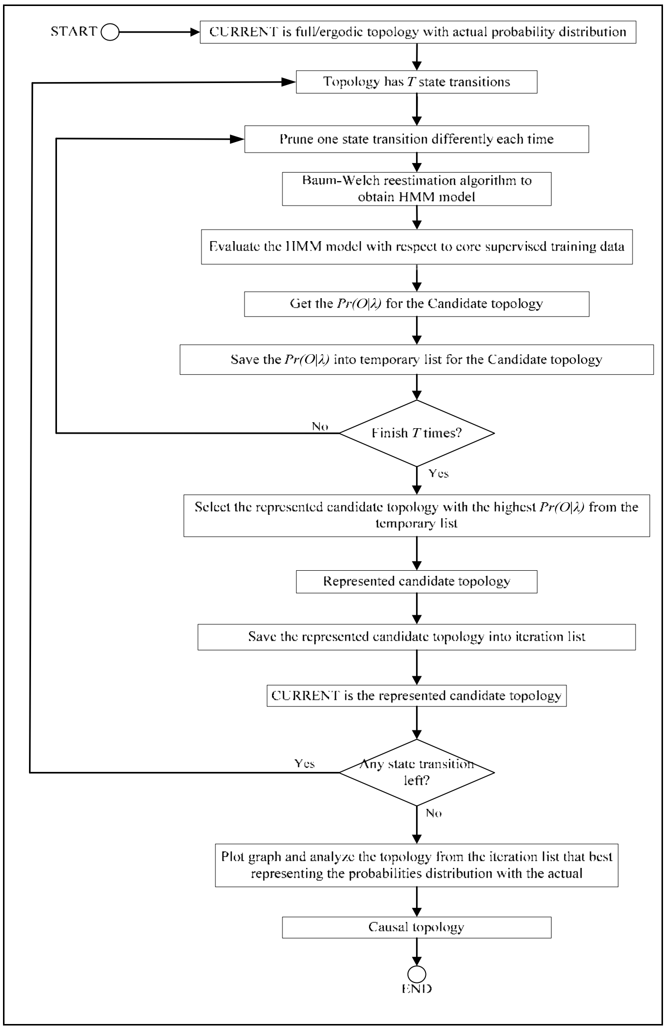

Figure 3. Iterative Pruning Algorithm Flow

Table 1. Candidate Topologies Values for Bridge Posture

Candidate Topology	Value
Bridge_Pruned_Round_1_Iterate_22.hmm	-148.6027391
Bridge_Pruned_Round_2_Iterate_0.hmm	-143.4247859
Bridge_Pruned_Round_3_Iterate_24.hmm	-142.464467
Bridge_Pruned_Round_4_Iterate_3.hmm	-141.9854173
Bridge_Pruned_Round_5_Iterate_10.hmm	-141.8789532
Bridge_Pruned_Round_6_Iterate_13.hmm	-142.7418304
Bridge_Pruned_Round_7_Iterate_10.hmm	-146.4061067
Bridge_Pruned_Round_8_Iterate_15.hmm	-141.2292823
Bridge_Pruned_Round_9_Iterate_10.hmm	-141.1256709
Bridge_Pruned_Round_10_Iterate_14.hmm	-140.6626432
Bridge_Pruned_Round_11_Iterate_15.hmm	-144.9474714
Bridge_Pruned_Round_12_Iterate_1.hmm	-145.341284
Bridge_Pruned_Round_13_Iterate_9.hmm	-145.0911842
Bridge_Pruned_Round_14_Iterate_12.hmm	-144.4233384
Bridge_Pruned_Round_15_Iterate_12.hmm	-143.5628722
Bridge_Pruned_Round_16_Iterate_6.hmm	-143.5106121
Bridge_Pruned_Round_17_Iterate_2.hmm	-144.1137385
Bridge_Pruned_Round_18_Iterate_5.hmm	-144.0817559
Bridge_Pruned_Round_19_Iterate_3.hmm	-144.7093785
Bridge_Pruned_Round_20_Iterate_4.hmm	-145.3390938
Bridge_Pruned_Round_21_Iterate_3.hmm	-145.9010206
Bridge_Pruned_Round_22_Iterate_6.hmm	-149.4806337
Bridge_Pruned_Round_23_Iterate_3.hmm	-165.6929415
Bridge_Pruned_Round_24_Iterate_4.hmm	-166.9633464
Bridge_Pruned_Round_25_Iterate_2.hmm	-163.6065685
Bridge_Pruned_Round_26_Iterate_1.hmm	-154.9168718

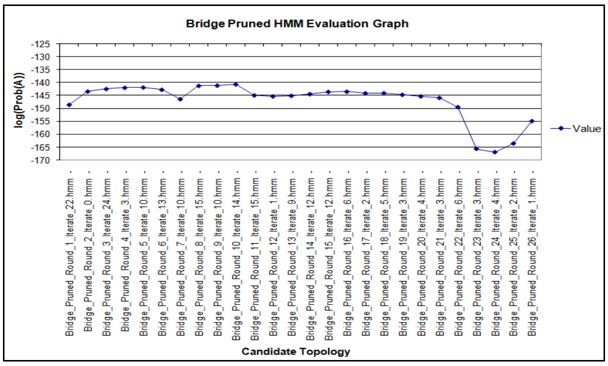

Figure 4. Bridge Posture Pruned Evaluation Result

After the pruning iteration completed, the represented candidate topology for each round is identified. A graph on the *Pr(O|λ)* versus iteration round is plotted to analyze the trend. The selection on the final represented candidate topology is based on the attained probability and the impact on the next topology's probability. If the removal of a state transition causes *Pr(O|λ)* to decrease substantially (drastic drop in the graph), the topology has been pruned beyond a structure that is appropriate for modeling the data. The simplest topology reached before a substantial decrease in *Pr(O|λ)* for a pruning iteration is the algorithm's estimate of the dynamic structure of the data. Table 1 and Figure 4 depicts the result on pruning iteration for bridge posture. The represented candidate topology is selected by inspecting the log probability value of each candidate topology in graph. In general, the represented candidate topology possesses the highest log probability and located before substantial probability drop at its neighbor candidate topology. The shaded row in candidate topology values tables below is the selected represented candidate topology.

IV. Implementation and Results

The implementation involved modeling two synthetic models (one male, one female) in six defined Yoga postures, namely bridge pose, chair pose, downward pose, supported shoulder stand pose, tree pose and warrior pose as shown in Figure 5. The target environment is a closed indoor environment with clean uncluttered background simulated by a tool. The causal HMM program performed characteristic view determination and iterative pruning process.

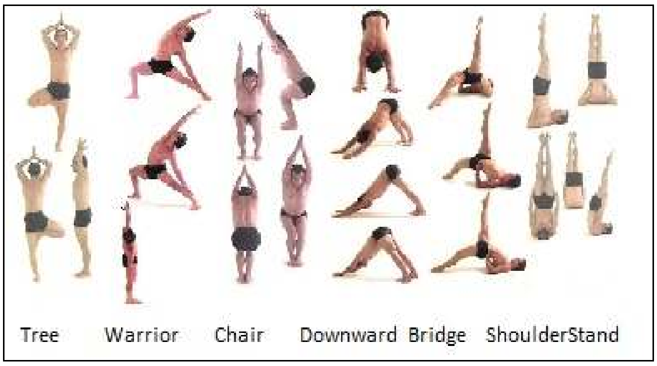

Figure 5. Yoga postures:tree, warrior, chair, downward, bridge and supported shoulderstand

The generated causal HMM for each posture are used to test against 50 testing image sets created with another two synthetic models. The testing image set contained images with object in different position translation. Some of the images have its partial object body captured outside of viewpoint. The object also varies in different size and scale due to position to camera viewpoint. Such behavior is intended to test the view independent feature of the pruned HMM with built-in characteristic views. Figure 6 shows causal HMM chair pose auto testing execution.

The recognition testing result is presented in confusion matrix in Table 2 (a) and (b). By comparing with full/ergodic topology HMM in (b), the pruned HMM in (a) achieved better result for accuracy, precision, sensitivity and specificity. Generally, all posture achieved outstanding result except the Bridge and ShoulderStand posture achieved low precision and sensitivity. This issue was not caused by pruning process because the ergodic HMM also encountered mismatch in this case. In fact, the issue was caused by the weakness in feature extraction. The gradient point-to-centroid approach didn't capture the image object shape comprehensively. The 12 dimension bin contour pixel boundary tracking did not check the shape information in horizontal and vertical perspective.

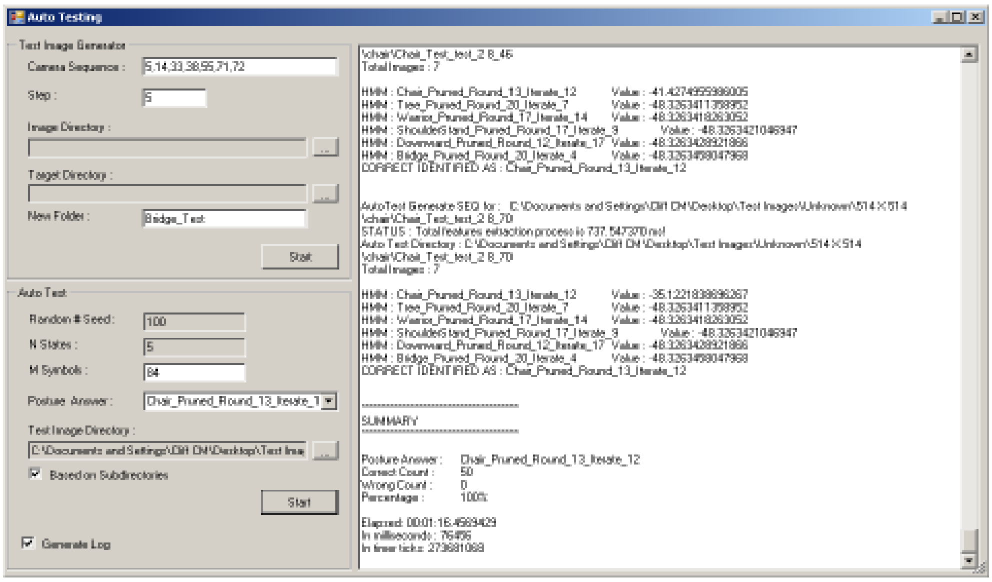

Figure 6. Causal HMM Auto Testing Execution

By comparing the ShoulderStand1 and Tree2 images' feature extraction graph as shown in Figure 7, the pattern was almost similar. This caused the K-Means clustering grouped it together and assigned with the same codeword for recognition. Thus, there was mismatch possibility for the ShoulderStand posture recognized as Tree posture. Somehow, this can be improved via projection-based and density-based feature extraction method.

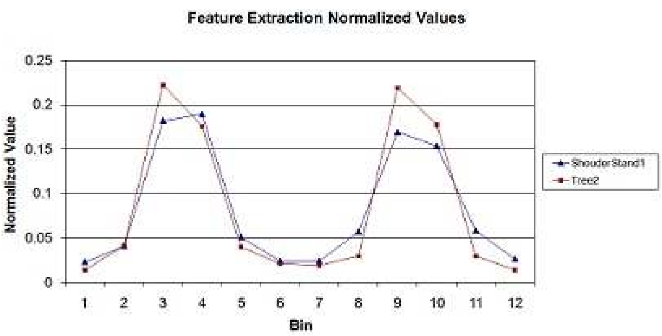

Figure 7. Graph on Normalized Feature Extraction Values for ShoulderStand1 and Tree2

The Table 3 displays the execution time needed to test the 50 image sets. From the mean execution time between ergodic and pruned HMM, there was no significant difference. This was due to the models were using the same number of hidden state in transition states (N states is 5). The matrix size for transition probability matrix, A and emission matrix, B are the same for pruned and ergodic HMM.

V. Conclusion

As majority of the posture recognition process using HMM with camera input is implemented in full complete topology, which means the number of cameras required in a closed/ predefined environment need to cover all angle viewpoint on the object comprehensively, it causes raise in cost issue. Moreover, it burdens the training time of the HMM. Such view dependency issue that results a series of camera needed yield the interest in designing causal HMM that integrated with characteristic view and states causal relationship discovery process.

Combining the above two approaches as hybrid solution to causal topology design for view independent multiple silhouette posture recognition is an innovation of this research. Moreover, it is the first attempt to apply such hybrid solution for HMM mechanism in posture recognition domain. The outcome is considered as one of the HMM variation, just like fuzzy HMM and neural network HMM. Understanding human action in an environment is a challenging task as it involves different granularity in its analysis and description according to the targeted application. Therefore, this research also fosters appreciation on all the previous works that had done by different parties in posture recognition domain to resolve various image processing and object recognition issues.

The causal HMM possesses the advantage for several potential applications such as Yoga E-learning classroom, old folk home monitoring and criminal act detection. Definitely, the posture that recognized by the system needs to be articulate and distinguishable. This is essential to avoid mismatch between defined postures. In average, causal HMM outperforms ergodic topology HMM in accuracy, precision, sensitivity and specificity. Undeniable, the characteristic view and iterative pruning process are effective in establishing and revealing the data relevance and cause. This is an initiative in data mining as it is extracts patterns from large datasets and leverages knowledge discovery.

Table 2. (a) Pruned HMM and (b) Ergodic HMM Confusion Matrix

(a) Pruned HMM Confusion Matrix

Postures	Bridge	Chair	Downward	ShoulderStand	Tree	Warrior	Accuracy	Precision	Sensitivity	Specific
Bridge	34	6	0	5	0	5	0.9267	0.8500	0.6800	0.9760
Chair	0	50	0	0	0	0	0.9667	0.8333	1.0000	0.9600
Downward	0	0	50	0	0	0	1.0000	1.0000	1.0000	1.0000
ShoulderStand	6	1	0	25	18	0	0.9000	0.8333	0.5000	0.9800
Tree	0	3	0	0	47	0	0.9300	0.7231	0.9400	0.9280
Warrior	0	0	0	0	0	50	0.9833	0.9091	1.0000	0.9800
						Means	0.9511	0.8581	0.8533	0.9707

(b) Ergodic HMM Confusion Matrix

Postures	Bridge	Chair	Downward	ShoulderStand	Tree	Warrior	Accuracy	Precision	Sensitivity	Specific
Bridge	15	6	0	13	7	9	0.8767	0.8824	0.3000	0.9920
Chair	0	50	0	0	0	0	0.9500	0.7692	1.0000	0.9400
Downward	0	0	50	0	0	0	1.0000	1.0000	1.0000	1.0000
ShoulderStand	2	5	0	32	7	4	0.8933	0.6957	0.6400	0.9440
Tree	0	4	0	0	46	0	0.9400	0.7667	0.9200	0.9440
Warrior	0	0	0	1	0	49	0.9533	0.7903	0.9800	0.9480
						Means	0.9356	0.8174	0.8067	0.9613

Table 3. Execution Time for 50 Dataset by Ergodic and Pruned HMM

HMM		Postures					
		Bridge	Chair	Downward	ShoulderStand	Tree	Warrior
Ergodic	Round 1 (milliseconds)	62460	64891	67060	65905	68781	64782
	Round 2 (milliseconds)	68175	66892	67998	63359	64280	66960
	Mean (milliseconds)	65317.5	65891.5	67529	64632	66530.5	65871
Pruned	Round 1 (milliseconds)	68284	63486	67132	61370	64308	62958
	Round 2 (milliseconds)	62707	67486	68000	67609	68816	69334
	Mean (milliseconds)	65495.5	65486	67566	64489.5	66562	66146

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