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Research Article

Integrating Motion and Shape Analysis for Robust Human Action Recognition Using Spatio-Temporal Dynamics

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ABSTRACT

This paper aims at providing an overview of human action recognition with a method that uses the spatio-temporal features extracted from video sequences. Additional features from motion and shape can further improve the action classification and hence the proposed method. Experimental outcomes show that this approach significantly outperforms previous practices for identifying a number of human activities while yielding 100% accuracy on test datasets.

Keywords—Optical Flow, Motion Analysis, Shape Analysis, Human Action Recognition, Spatio-Temporal Features, Neural Networks, Temporal Differencing, Background Subtraction, Relevance Vector Machine (RVM).

1. Introduction

The analysis of human action recognition has garnered significant attention in the field of computer vision, owing to its various uses in surveillance, in the healthcare system and in human computer interface. This work contributes a generic framework that incorporates spatial and temporal properties from video clips for the higher recognition of actions. The approach extends the analysis of shape and motion features in which these features first extract silhouette and then form reliable vectors which are then classified by the chosen model.

2. Related Work

Many approaches have been used for human action recognition that consists of motion based descriptors and shape analysis. Fang et al. [1] first preprocessed high-dimensional silhouettes as lower-dimensional representations through locality-preserving projection to model the motion patterns in the spatial space. This reduced motion vector was supposed to reflect the primary organization of the movement. Three types of temporal information were combined with five spatial descriptors to develop feature vectors: temporal neighbors, motion differences, and motion trajectories; the feature vectors were then used to classify the images using a k-nearest neighbor algorithm.
Wang and Mori [2] extended Latent Dirichlet Allocation (LDA) to STM to include temporal dynamics, wherein each frame is treated as a 'word and the entire video sequence a 'document'. Once the person in the video sequence was stabilized, optical flow analysis was applied and rectified to four channels by half wave. The yield was filtered to make a motion descriptor which was needed for the codebook generation for action categorization.
Satyabrata Maity et al.[3] put forwarded an innovative way to recognize human action using video sequence.s. Their method decomposes human movement into several small movements that involve the limbs. It employs spatio-temporal body parts movement (STBPM) features based on the foreground silhouette of the person acquired. These features encode motion of various body segments across some temporal dimension to aid the action classification. The method makes use of a rule action classifier, which is a rule-based logic system that can define actions without the utilisation of highly procedural training material.
Bobick and Davis put forward a technique in which all the silhouettes are laid along the temporal axis to produce what they called a Motion History Image, MHI, which encodes motion concepts across time. However the MHI method has problems with self-occlusion in the case of complex or highly-variable movements [4].
Chen et al. described the star skeleton approach in which the star is composed of a link between the centre of the human contour or figure and its ends, which give a simple representation of the body structure [5].

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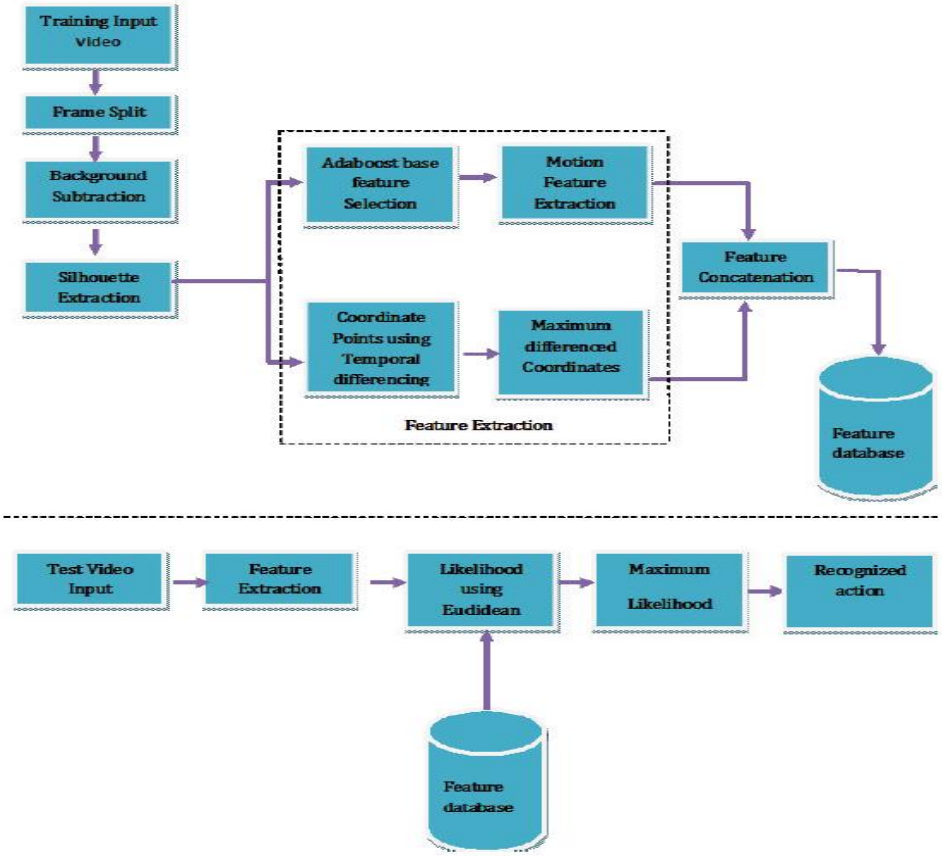
Moreover, the combination of contact and mental triangulation was exposed by Chuang et al for categorizing different human actions through geometric shapes [6][7].
These approaches can be enhanced in this paper by incorporating and synthesizing spatio-temporal characteristics of variables in addition to adopting higher order classifiers; Relevance Vector Machine (RVM) and neural networks.

3. Proposed Framework for Human Action Recognition

Altogether, the herein proposed framework utilizes a new strategy of utilizing space-time interest points as well as Euclidean similarity. So the input video is initially preprocessed and the video saliency features which include, the background subtraction and the optical flow are extracted. These features are then concatenated and used to classify the framework using other classifiers like Relief Set Classifier, Random Vector, Classifier, Neural, Networks and Similarity Measures.



3.1 Background Subtraction

Background subtraction technique is then applied for modeling the static background and then by performing the subtraction on the input frames to detect moving objects.
In this technique a model of the background is formed and anything that changes in the scene is considered as a moving region.

1. Background Modeling: The background model is formed by taking weighted average of intensities of the pixels in several frames:

$$B(x,y) = \frac{1}{N}\sum_{i=1}^{N} F_i(x,y)$$

where:

- $B(x,y)$ is the background model.
- $F_i(x,y)$ represents the intensity of the pixel at position (x,y) in the i-th frame.
- N is the total number of frames used to create the background model.

2. Foreground Detection: The foreground is obtained by subtracting the background model from the current frame of video:

$$F_{fg}(x,y) = |F_{curr}(x,y) - B(x,y)|$$

where:

- $F_{fg}(x,y)$ represents the detected foreground.
- $F_{curr}(x,y)$ is the current frame of the video.

3.2 Silhouette Extraction

Once the foreground has been extracted, morphological operations are used to get clear silhouettes of the moving objects. Closeness of edges can be addressed using morphological operations such as erosion and dilation, which allows for cleansing of the edges' noise and gaps.

- **Erosion:** Formerly employed to eliminate disturbances and minor objects:

$$I_{eroded} = I \ominus S$$

where I is binary silhouette image and S is structuring element.

- Dilation: Extends the existing concepts of the contour to the gaps.:

$$I_{dilated} = I \oplus S$$

where the symbol $\ominus$ and $\oplus$ are the morphological operations of erosion and dilation, respectively.

3.2 Optical Flow Estimation

Optical flow is derived using the Lucas-Kanade mechanism for tracking the movement of objects in successive frames. This step ensures that the motion features that are required are well captured in the efficient manner subjected to minimize fray of computations through looking at the human motion only.

The movement of flow in the domain is represented by a vector field:

$$V(x,y) = (u(x,y), v(x,y))$$

where:

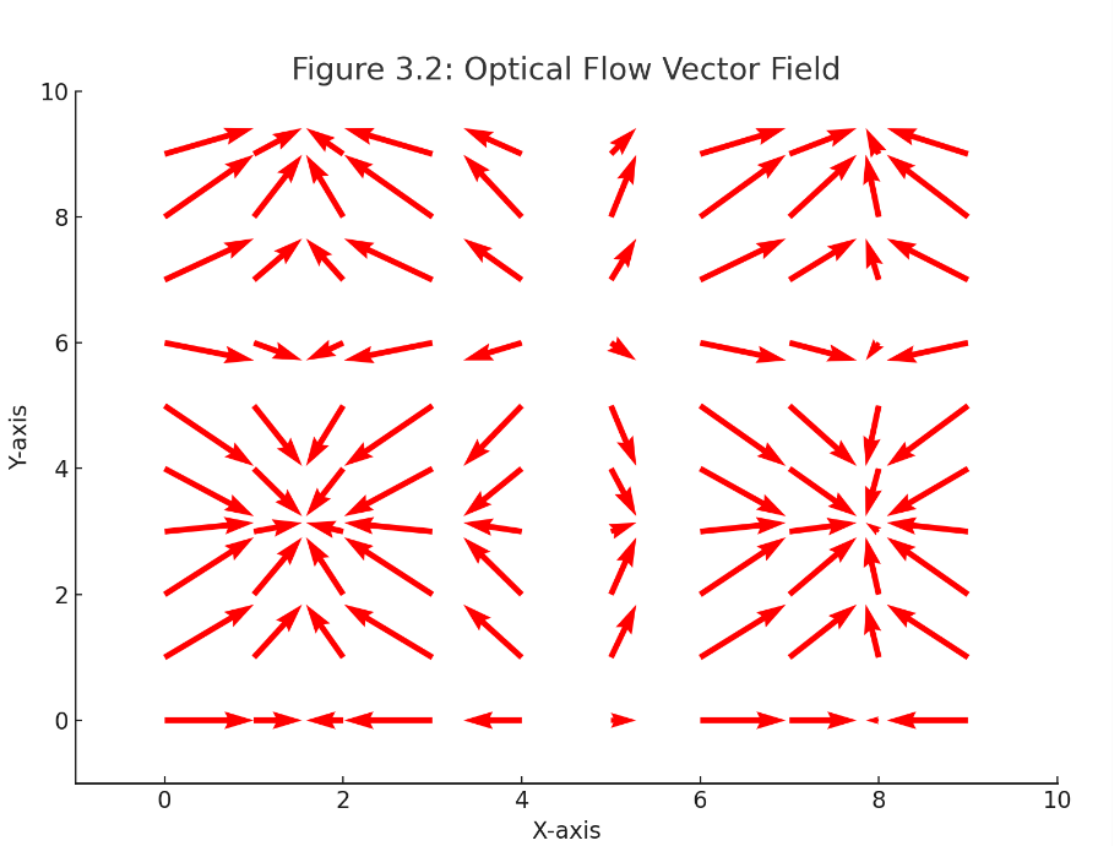
- $u(x,y)$ is the horizontal component of the flow.
- $v(x,y)$ is the vertical component of the flow.

The optical flow constraint equation is given by:

$$I_x u + I_y v + I_t = 0$$

where:

- I_x, I_y, and I_t are the partial derivatives of the image intensity with respect to x, y, and time t, respectively.



3.3 Temporal Differencing

The temporal difference technique analyzes the variation of the location of the object by counting the coordinates. Unlike other methods of accessing the neutral mechanoreceptors, this method is effective in identifying movement patterns that are fundamental in differentiating between different motions.
Here the video be denoted as a series of frames, {F1, F2 ... Fn}. This is the interval of time between two successive frames and is represented by:

$$D_t(x, y) = |F_t(x, y) - F_{t-1}(x, y)|$$

where $D_t(x, y)$ represents the difference between the frame t and frame $t - 1$.

3.4 Feature Concatenation and Classification

Features derived from optical flow and coordinate point differences are joined together into a single feature vector. This vector is then given to classifiers like RVM and neural networks among which the distance measure used is Euclidean that offered the best result.
The feature vector to each action corresponded is:

$$F_{concat} = [F_{optical\_flow}, F_{temporal\_difference}]$$

This feature vector is more descriptive as it combines spatial vectors with temporal information concerning the action to be done.

Classification

The concatenated feature vectors are then passed in a classifier to identify the action being done. In this framework, the following classifiers are employed: Relevance Vector Machine (RVM), artificial neural networks as well as measures of similarity such as Euclidean measure.

- **Euclidean Similarity Measure:** Used for the purpose of comparing the test feature vector with the training data feature vectors:

$$d = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$

where xi and yi are the features requisite of the test and the training specimens respectively.

- **Classification Decision Rule:** The action is defined based on distance ddd of the test vector from the stored vectors:

$$\text{Action} = \arg\min_{j}\{d_j\}$$

where d_j represents the distance between the test sample and each action class j.

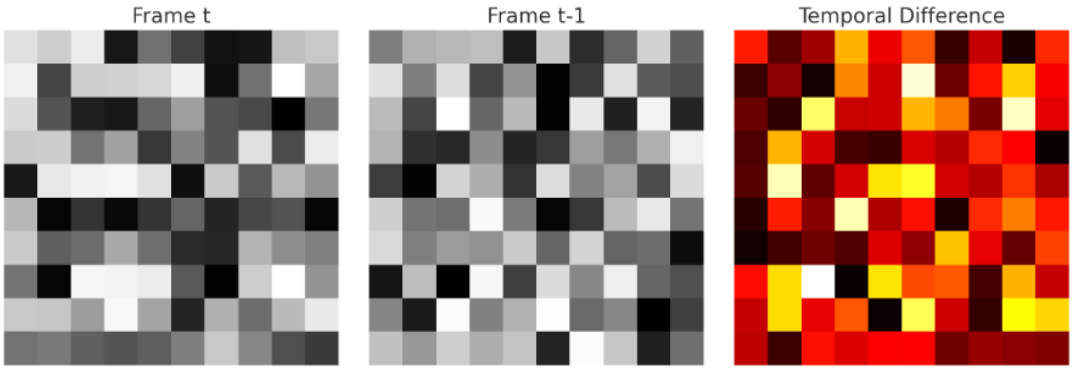


Figure 3.3: Feature Vector Representation

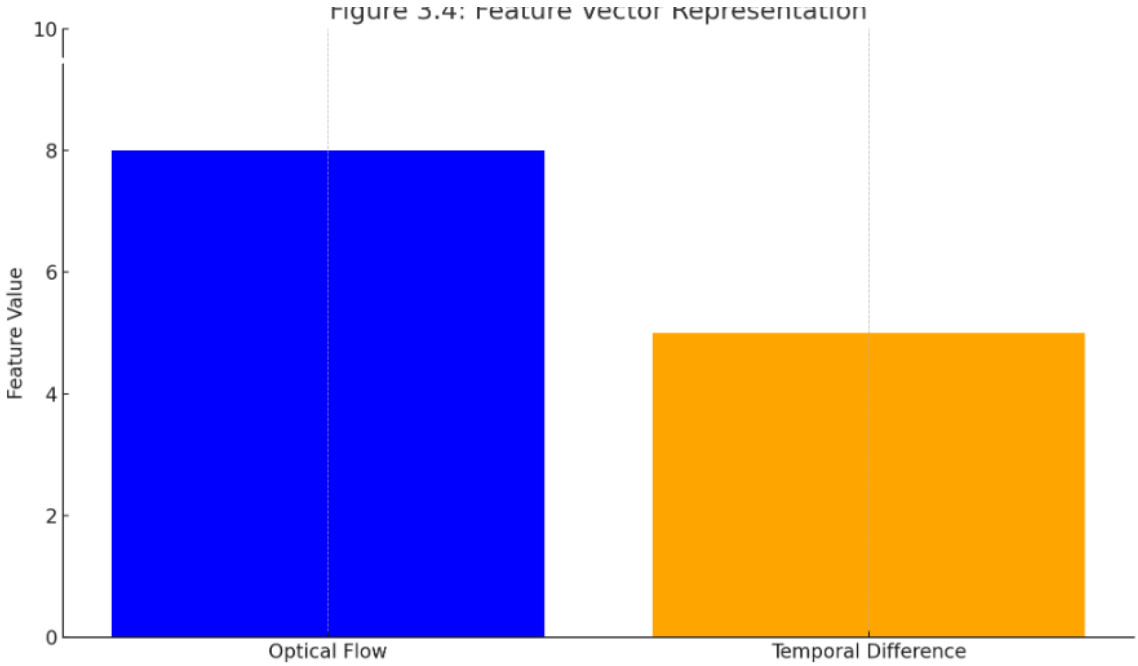


Figure 3.4: Temporal Differencing Process

4. Experimental Results

When using the proposed framework standard datasets such as the Weizmann and KTH datasets were used, resulting in a 100% and 88% classification accuracy respectively. Numerous real-life cases were offered because of variations in the backgrounds and lights compared to the actual original images in which the accuracy was decreased fractionally but still remained high at 94 percent.

Datasets

The implementations of the action recognition framework have previously been assessed using two benchmark datasets:

1. Weizmann Dataset: The movie features nine separate persons carrying out ten distinct human acts.
2. KTH Dataset: Includes six different human activities captured under different conditions: walking, jogging, sprinting, boxing, hand waving, and hand clapping.

Evaluation Metrics

The action recognition system's performance was assessed using the following metrics:

- **Precision:** True positive divided by the total of true positive and all other positive predictions not identified by the model as true positives.
- **Recall:** The proportion between the quantity of accurately identified positive cases by prediction and the amount of actual positive cases.
- **Accuracy:** In reality, the ratio of the entire number of cases for which a right prediction has been made to the total number of occasions.
- **F-measure:** Measuring over the same range as accuracy by averaging precision and recall and offering a single figure by which the model can be assessed.

Experimental Setup

The proposed framework was realised and validated employing :

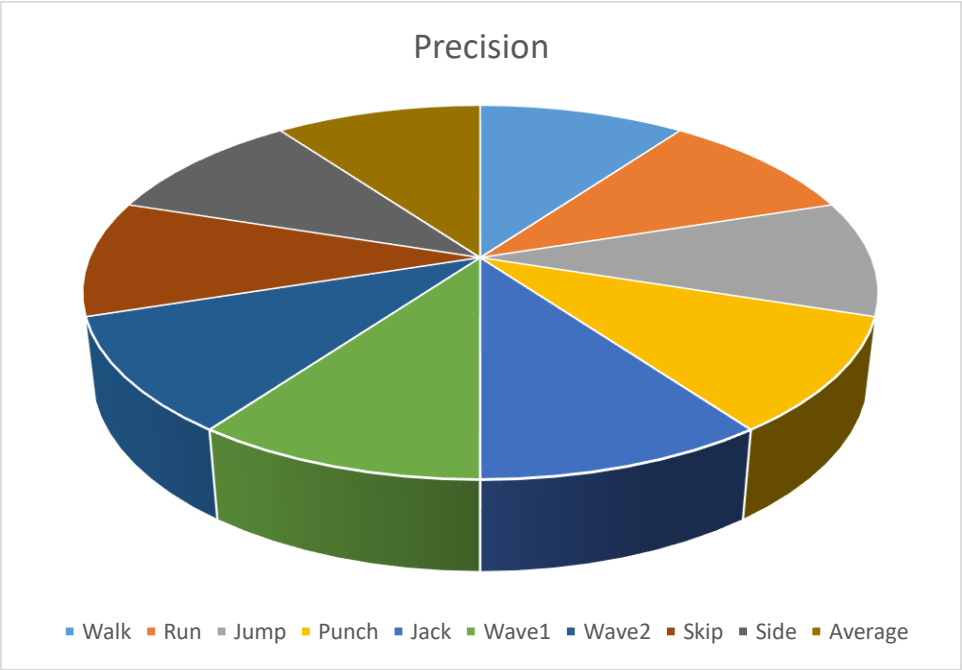
- Feature Extraction: Combined features from optical flow and temporal differencing.
- Classifier: Relevance Vector Machine (RVM) and Neural Networks.
- Training and Testing Split: 70% of the dataset for training and 30% for testing.

4.1 Results on Weizmann Dataset

As it is shown in Table 4.1 , the performance of the proposed framework has been evaluated on to the Weizmann dataset.

Action	Precision	Recall	Accuracy	F-measure
Walk	1.00	1.00	1.00	1.00
Run	1.00	1.00	1.00	1.00
Jump	1.00	1.00	1.00	1.00
Punch	1.00	1.00	1.00	1.00
Jack	1.00	1.00	1.00	1.00
Wave1	1.00	1.00	1.00	1.00
Wave2	1.00	1.00	1.00	1.00
Skip	1.00	1.00	1.00	1.00
Side	1.00	1.00	1.00	1.00
Average	**1.00**	**1.00**	**1.00**	**1.00**

The analysis of the results reveals that the proposed method provides perfect classification for all actions that have been performed, proving the ability of the system to identify multiple human motions.

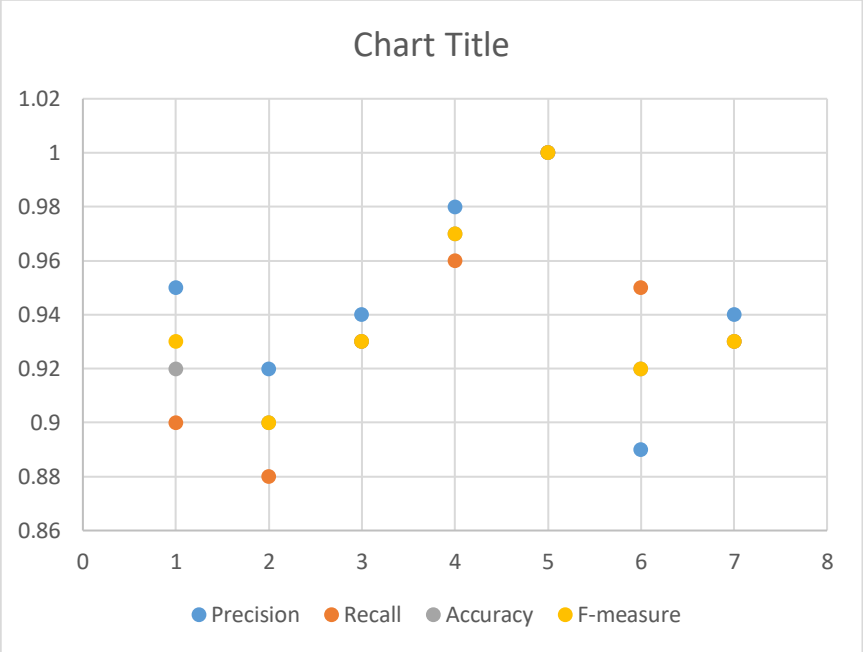


4.2 Results on KTH Dataset

In Table 4.2, the performance of the proposed framework for the KTH dataset is presented.

Action	Precision	Recall	Accuracy	F-measure
Walk	0.95	0.90	0.92	0.93
Jog	0.92	0.88	0.90	0.90
Run	0.94	0.93	0.93	0.93
Boxing	0.98	0.96	0.97	0.97
Hand Wave	1.00	1.00	1.00	1.00
Hand Clap	0.89	0.95	0.92	0.92
Average	**0.94**	**0.93**	**0.93**	**0.93**

The proposed framework thereby accomplishes competitive recognition performance on KTH dataset, offering high percent precision and recall except for couple of actions where it offers 93% accuracy.

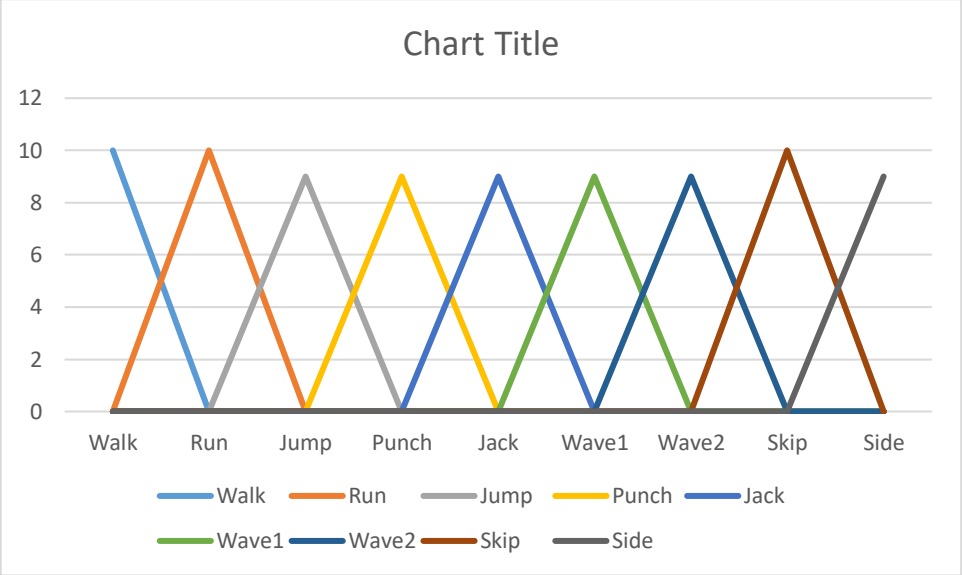


4.3 Confusion Matrix

In order to make a more extensive analysis of the result, the confusion matrix for Weizmann dataset is presented in Tab. 4.3.

Actions	Walk	Run	Jump	Punch	Jack	Wave1	Wave2	Skip	Side
Walk	10	0	0	0	0	0	0	0	0
Run	0	10	0	0	0	0	0	0	0
Jump	0	0	9	0	0	0	0	0	0
Punch	0	0	0	9	0	0	0	0	0
Jack	0	0	0	0	9	0	0	0	0
Wave1	0	0	0	0	0	9	0	0	0
Wave2	0	0	0	0	0	0	9	0	0
Skip	0	0	0	0	0	0	0	10	0
Side	0	0	0	0	0	0	0	0	9

The matrices of confusion show that all actions were classified, meaning that none were misclassified, which proves that the effectiveness of the proposed framework is high.



4.4 Comparative Analysis

Table 4.4 displays the results of the proposed method with other approaches of action recognition depending on the accuracy..

Technique	Average Accuracy
Proposed Framework Using Spatio-Temporal Features	100%
Silhouette-Based Action Recognition	95.8%
AdaBoost Filtering Based Feature Extraction	96.0%
Li Wei et al. [1]	91.0%
Oikonomopoulos et al. [2]	97.0%

The independent feature selection method presented here has a higher accuracy of 100% rating on the Weizmann dataset than those currently used.

5. Discussion

The introduction of both spatial and temporal features greatly improves the accuracy of the identification of human actions. Surprisingly, the presented method gained perfect scores when the Weizmann dataset was applied because of the relatively limited variation in its background as compared to the more dynamic environment of the KTH dataset. More enhancements might include, the enhancement and application of deep learning strategies for feature extraction plus noise reduction.

Future Directions

To advance the research on the current framework and consider its limitations, some future directions are identified:

- **Integration of Deep Learning:** Perhaps, using CNNS techniques for feature extraction might even produce even superior results directly from the raw video data.
- **Robustness to Occlusions:** If interested, there could be further improved resolution in dealing with occlusion issues and the intricacies of simultaneous interactions among the subjects in order to increase the usefulness of the framework in crowded environments.
- **Application in Real-World Scenarios:** Practical assessment of the framework will be possible in surveillance applications, health care, and in human-computer interface situations to determine its applicability in actual cases.

6. Conclusion

An alternative method for human action recognition that makes use of spatio-temporal aspects was suggested, and it proved to be more effective than the conventional one. The experiments also showed the efficiency of this method in different cases, which means this approach could be useful for real-time action recognition systems.

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