Human Action Invarianceness for Human Action Recognition

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***Abstract*—The uniqueness of the human action shape or silhouete can be used for the human action recognition. Acquiring the features of human silhouette to obtained the concept of human action invarianceness have led to an important research in video surveillance domain. This paper discusses the investigation of this concept by extracting individual human action features using integration moment invariant . Experiment result have shown that human action invarianceness are improved with better recognition accuracy. This has verified that the integration method of moment invariant is worth explored in recognition of human action in video surveillance**

***Keywords*—Human Action Recognition, human action invarianceness, Integration Moment Invariant**

I. INTRODUCTION

Human action recognition (HAR) has become essential parts of many computer vision applications, and it involves a series of processes such as image data acquisition, feature extraction and representation and classification for recognition [1-2]. The action classification is crucial in recognizing the human action because the extracted features of the motion must be classified accordingly. The increasing number of action classification in a video will lead to more challenges due to the higher overlapping between classes. Random movements cause scattered data, and consequently, these problem cause the features are not labeling action class correctly and representation of data features are not standardize properly [3-5]. This shows that inappropriate feature extraction and representation may directly cause a low accuracy in classification of human action. Based on the literatures, many studies have been done on global approach for feature extraction. Global representations are powerful since much of the information is encoded, as they focus on global information. The conventional global based moment invariant that was put forward by [6], Geometric Moment Invariant (GMI), was widely used for feature extraction and classification in human action recognition [6]. This method has a unique characteristic in identifying an image due to its invariant to orientation, size and position of the shape image. However, in terms of the invarianceness characteristic of human still have some weaknesses. The most important characteristic of invariance of the human action is the stability under different views but distinctive from the different classes. Consequently, this method leads some issues, especially in terms of the complexity of data feature representation during the process of feature extraction in term of intra-class and inter-class variance. The weaknesses of GMI are includes:

i. Reliant and incomplete invariant under translation, rotation and scaling[7].
ii. Lost scale invariant in discrete condition [8].
iii. Applied only a small subset of moment invariant [9].
iv. Produce errors if the transformations are subjected to unequal scaling data transformation [10-18]
v. Data position of pixel is far away from centre coordinate [19]
vi. Problem in region, boundary and discrete condition [20]

Therefore, more standardize uniform representation of data distributions are needed for recognition of human action. In this paper, a human action invarianceness (HAI) is present using feature extraction techniques and representation methods based on the integration of moment invariant called Higher United Moment Invariant (HUMI); the function is introduced in order to replace the conventional Geometrical Moment Invariant (GMI). A good feature extraction approach should be able to generalize over variations within class (intra-class) and distinguish between actions of different classes (inter-class). Therefore, the variation of the features of human action can be minimize variation for intra-class and maximize variations for inter-class for human action. The human features representation is then improved with the invariant discretization method in order to raise the performance of the system and standardize the amount of accessible information to a manageable size of feature vector representation without losing any valuable information

The paper is systemalized as follows. Human action is explained in section 2. Followed with the Human action invarianceness through intra-class and inter-class concept in section 3. Section 4 describes the proposed integration of moment process in this work. The experiment result is discussed in section 5. And finally, the conclusion is drawn in section 6.

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II. HUMAN ACTION

Human Action is considered as the classification of time varying feature data, such as matching unknown sequence with a group of labeled sequences representing typical actions. Human silhouette data contains different number of frames in different actions and located at different places. It is difficult to determine the invarianceness distance as close as possible when the person is in motion. Moreover, the center of the silhouette moves due to actions and different view sets. The multitude of action features can either be based on shapes or motion; in this paper, the focus of features extraction is based on the shapes features. Generally, the image is basically based on the binary image. Black pixel represents the background and white pixel represents the foreground of an image, as shown in Fig. 1.

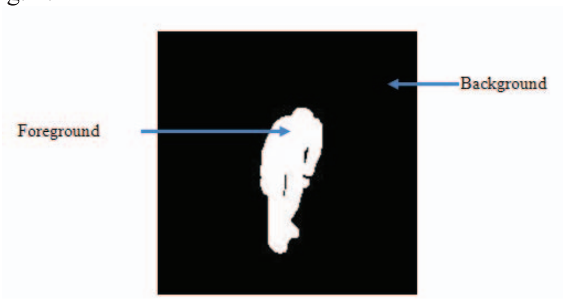

Fig. 1 Background and foreground pixel of the image frame.

Hence, the features that describe the human body silhouette could capture the shape characteristics of the human subject, either region or boundary representation of an action, over time by using the proposed approach. These features then form a main source of information, especially with regards to the interpretation and understanding of human action based on image sequence. Therefore, the invarianceness concept is important when trying to recognize human action that has many variations of the same action under certain transformations, such as translation, scaling and rotation.

III. HUMAN ACTION INVARIANCENESS

The invarianceness of the human action is very important as most action features based on silhouettes are dependent on the movement of the silhouette in the image space. Human action invarianceness (HAI) is defined as the *preservation of an image regardless of its transformations, where it gives small similarity error for intra-class of action (same action) and large similarity error for inter-class of action (different actions).*

A. Human Action Invarianceness Procedure

HAI procedure consist of three processes: extracting global features from moment representation, similarity measurement of the variance between features, and intra-class and inter-class analysis, as illustrate in Fig. 2. The incorporation of features is considered essential in order to handle the task of recognition of human actions performed by different people, especially in intra-inter class variations [21]. These representation features are form as invariant feature vectors of the image frame resulting from the feature extraction task.

B. Feature Extraction

Feature extraction is a fundamental source of information regarding the interpretation of specific of human action, generally viewed as the core and time consuming part in any action recognition systems [22].

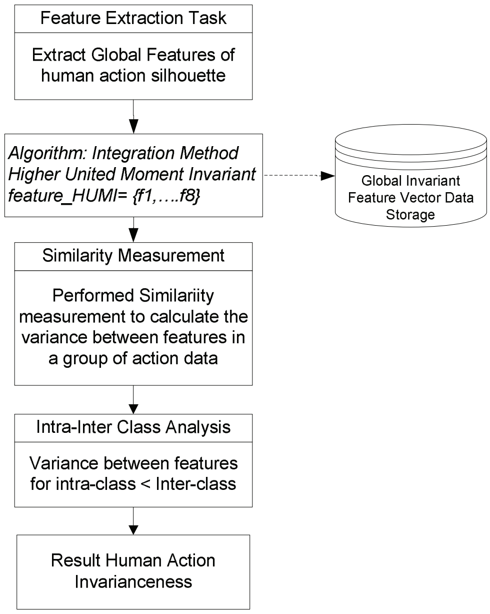

Fig. 2 Human Action Invarianceness Procedure

The process of feature extraction in human action involves transforming the input data that describe the shape of a segmented silhouette of a moving person into the set of represented features of action poses. The quality of the extracted features is demonstrated by the success of the relatively simple classification scheme that could be achieved basically by reducing the form instead of full representation to the relevant information [23]. Low performance in terms of accuracy is due to the various features that represent the same action, and this makes the recognition process difficult and complex. Similar characteristics of action behavior are easy to recognize if all of the different features value for similar action has a standard representation for generalized unique features of human action, which consequently makes the recognition process easier. Therefore, illustration of human action features is required to represent the action unique features in a systematic feature representation. The main extracted feature consists of the feature vector that will be used for silhouette classification in its respective classes. As each frame sequence represents a corresponding class of human action, the intra-class variance is small and inter-class variance is larger. Variations between samples are found by calculating the MAE of all samples in the set.

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C. *Intra-class and inter-class for Human Action Invarianceness*

Two issues need to be addressed when comparing human action variance: the variability of the human action of the same or different person with the same actions, and the variability of the human action of the same or different person with different actions to another. Invarianceness of human action concepts is proven with the lower variance between features (similarity error) for intra-class (same action image) and higher variance in inter-class (different action image), which is due to the uniqueness of the extracted features. MAE function is one of the statistical functions used for measuring the similarity error by calculating the absolute value of mean variance from the reference data. The equation of MAE is shown as below:

$$MAE = \frac{1}{n}\sum_{i=1}^{f}|(x_i - r_i)|$$

Where n is the number of image frame; x_i is the current image frame; r_i is the reference image frame (first image frame is the reference image); f is the number of features image frame; i is the feature's column of image frame

The smallest MAE value is considered as the most similar to the original action image, which is the reference image to be compared. On the contrary, the highest MAE value is the most different action. Therefore, the range of MAE between intra-class and inter-class is not a concern as long as it proves the characteristics of human action recognition concepts (the intra-class value must be lower than inter-class values). Mean absolute error (MAE), performed in this work as the similarity measurer in HAI to find the mean of variance between features in a group of data action.

IV. Integration Moment Invariant

The volumes of image frames are characterized by 2D geometrical moments, which will be used as an input for recognition process. 2D of actions image is converted to $f(x,y)$ by translating, rotating and scaling in an action cycle of the video sequence. The integration moment invariant presented in this paper called Higher United Moment Invariant (HUMI). Higher order Scaled United Moment Invariant (HUMI) has presented by [12]. HUMI can be achieved with the fusion formulation of embedding improvement for scaling factor HGMI from [17] into the UMI from [20]. UMI presented eight formula as shown below.

$$\theta_1 = \sqrt{\theta_2}/\theta_1 \qquad \theta_2 = \sqrt{\theta_6}/\theta_1\,\theta_4$$
$$\theta_3 = \sqrt{\theta_5}/\theta_4 \qquad \theta_4 = \sqrt{\theta_5}/\theta_3\,\theta_4$$
$$\theta_5 = \theta_1\theta_6/\theta_2\,\theta_3 \qquad \theta_6 = (\theta_1 + \sqrt{\theta_2})\theta_3/\theta_6$$
$$\theta_7 = \theta_1\theta_5/\theta_3\,\theta_6 \qquad \theta_8 = (\theta_3 + \theta_4)/\sqrt{\theta_5}$$

Where θ_1 through θ_6 are unchanged under the image scale, translation and rotation. Meanwhile, θ_7 is for skew invariant that can detect image under reflection. For the θ_8 is change based on the regions, boundaries, and discrete condition

The derivation formulation of the HUMI is given as in Theorem 4.1 below;

Theorem 4.1 To normalise the central moment, the equation is based on GMI using Equation (1);

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{pq}^{\frac{p+q+2}{2}}} \tag{1}$$

Where η_{pq} is definition for unequal scaling factor.
Then for the discrete condition, the equation is based on Equation (2);

$$\eta_{pq} = \left(\frac{\mu_{20}{}^{(p+1)/2}\mu_{02}{}^{(q+1)/2}}{\mu_{40}{}^{(p+1)/2}\mu_{04}{}^{(q+1)/2}}\right)\mu_{pq} \tag{2}$$

Next for a boundary representation, the equation is based on Equation (3);

$$\eta''_{pq} = \frac{\mu_{pq}}{(\mu_{00})^{p+q+1}} \tag{3}$$

There are three steps outlines that can be used to explain the integration process of HUMI.

Step 1: As an example, consider θ_1 in UMI, where $\theta_1 = \sqrt{\theta_2}/\theta_1$. From Hu Moment Invariant, θ_2 as given in Equation (1), $\theta_2 = (\eta_{20} + \eta_{02})^2 + 4\eta_{11}^2$. Substituting θ_1 into θ_2, where $\theta_1 = \eta_{20} + \eta_{02}$ will result in Equation (4):

$$\theta_2 = \left(\frac{\mu_{20} + \mu_{02}}{\mu_{00}^2}\right)^2 + \frac{4\mu_{11}^2}{\mu_{00}^4} \tag{4}$$

Then substituting Equation (1) into Equation (4) will result Equation (5):

$$\sqrt{\theta_2} = \frac{\sqrt{(\mu_{20} + \mu_{02})^2 + 4\mu_{11}^2}}{\mu_{00}^2} \tag{5}$$

And

$$\theta_1 = \frac{\mu_{20} + \mu_{02}}{\mu_{00}^2} \tag{6}$$

Therefore,

$$\sqrt{\theta_2}/\theta_1 = \frac{\sqrt{(\mu_{20} + \mu_{02})^2 + 4\mu_{11}^2}}{\mu_{20} + \mu_{02}} = \theta_1 \tag{7}$$

Step 2: Consider θ'_1. From the Hu formulation, $\theta_2 = (\eta_{20} + \eta_{02})^2 + 4\eta_{11}^2$, as expressed in Equation (1), then θ'_1 is given by Equation (8):

$$\theta'_1 = \frac{\mu_{20}}{\mu_{00}^3} + \frac{\mu_{02}}{\mu_{00}^3} \tag{8}$$

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Therefore,

$$\sqrt{\theta_2}/\theta_1 = \theta''_1 = \frac{\sqrt{(\mu_{20} + \mu_{02})^2 + 4\mu_{11}^2}}{\mu_{20} + \mu_{02}} \quad (9)$$

Hence, it can be concluded that

$$\theta_1 = \theta'_1 = \theta''_1 \quad (10)$$

The moment invariant based on the changes of scaling and orientations are recorded, and the results of the image frame variation are compared.

V. EXPERIMENTAL RESULTS

A. Action Invarianceness

This section compares and discusses the results obtained from all techniques in order to evaluate the capability of the proposed technique and to determine the best technique for human action recognition. Similarity errors for intra-class (same actions) is lower than inter-class (different actions). The experiments are divided into two categories, which are intra-class and inter-class. Both classes are necessary in order to find the best solution for human action in recognition. In this study, the results of intra-class analysis based on MAE are analyzed. The INRIA Xmas Motion Acquisition Sequence is known as IXMAS is used during experiment. IXMAS dataset contains 13-daily motions perform by 10 actors. This publicly available dataset is frequently updated and accessible online. The experiment are based on 30 frames, 120 frames and 300 frames of action sequence for 13 human actions, which are “check watch” (cw), “cross arms” (ca), “scratch head” (sh), “sit down” (sd), “get up” (gu), “turn around” (ta), “walk” (wk), “wave” (wv), “punch” (pc), “kick” (kc), “point” (pn), “pick up” (pu), and “throw” (th). Example of MAE calculation is presented in Table I. Feature 1 to feature 8 are extracted invariant of each frame of action 'get up'. The invariancesness of each action 'get up' can be interpreted from the given MAE values with the same reference image (first image). The small errors signify that the image is close to the original image. An average of MAE is taken as the value of overall results.

TABLE I. HIGHER UNITED MOMENT INVARIANT FOR ACTION 'GET UP'

image	**f1**	**.......**	**f7**	**f8**	**Mean Error**
386	0.00226	....	1.50066	1.05459	-
....	....	....	......	....	
408	0.00508	....	0.81782	0.72771	0.27461
....	....	....	....	....	....
545	0.00542	....	2.02869	1.31867	0.47849
				Average MAE	**0.251033**

Table II illustrates the comparison MAE values for GMI and HUMI based on intra-class through 13 human action, respectively. Meanwhile, Table III show the result comparison between GMI and HUMI based on inter-class invarianceness.

TABLE II. INTRA-CLASS BASED ON MAE FOR HUMAN ACTION INVARIANCENESS FOR 13 HUMAN ACTION FOR 13 HUMAN ACTION

Action	Moment Invariant	Intra-class 30 frames	Intra-class 120 frames	Intra-class 300 frames
Check watch	GMI	0.7119	0.26952	0.11869
	HUMI	**0.76465**	**0.37515**	**0.14954**
Cross Arm	GMI	0.56374	0.3466	0.13622
	HUMI	**0.4489**	**0.24031**	**0.10264**
Scratch Head	GMI	**0.67004**	**0.333**	**0.15363**
	HUMI	0.91191	0.46336	0.19284
Sit Down	GMI	0.74628	0.33256	0.13599
	HUMI	**0.37159**	**0.18421**	**0.06949**
Get Up	GMI	0.67391	0.29768	0.1069
	HUMI	**0.33691**	**0.21259**	**0.08732**
Turn Around	GMI	0.66343	0.35452	0.17316
	HUMI	**0.46589**	**0.21395**	**0.08326**
Walk	GMI	1.33916	0.71876	0.26423
	HUMI	**0.39808**	**0.19687**	**0.06584**
Wave	GMI	0.80022	**0.40578**	0.17034
	HUMI	**0.7847**	0.40793	**0.16852**
Punch	GMI	0.72187	0.45279	0.1646
	HUMI	**0.48509**	**0.22589**	**0.09218**
Kick	GMI	0.63828	0.33489	0.11701
	HUMI	**0.505**	**0.25015**	**0.09789**
Point	GMI	0.88025	0.38384	0.18573
	HUMI	**0.48268**	**0.2555**	**0.10081**
Pick Up	GMI	0.5252	0.40925	0.13275
	HUMI	**0.46549**	**0.23416**	**0.08529**
Throw	GMI	0.31406	0.48527	0.2281
	HUMI	**0.59449**	**0.30951**	**0.1223**

TABLE III. INTER-CLASS HUMAN ACTION INVARIANCENESS

Action	GMI	HUMI
Chek watch vs Cross Arm	0.85908	**0.81130**
Check watch vs Scratch Head	0.73443	**0.09188**
Check watch vs sit down	0.85779	**0.61469**
Check watch vs get up	1.25152	**0.85655**
Check watch vs turn around	0.66440	**0.63327**
Check watch vs walk	0.27865	**0.36521**
Check watch vs wave	**0.41178**	0.62015
Check watch vs punch	**0.42613**	0.51980
Check watch vs kick	1.34289	**0.12576**
Check watch vs point	0.40706	**0.23099**
Check watch vs pick up	0.80411	**0.34086**
Check watch vs throw	0.72230	**0.49944**

The graph comparison of the result based intra-class invarianceness and inter-class invarianceness is presented in Fig. 3 through Fig.5. To get more significantly about the invarianceness of the proposed integration method, the result based on standard deviation of intra-class invarianceness using 13 human action is presented. The result of the standard deviation is shown at Table IV respectively. And the graph is illustrated at Fig. 6

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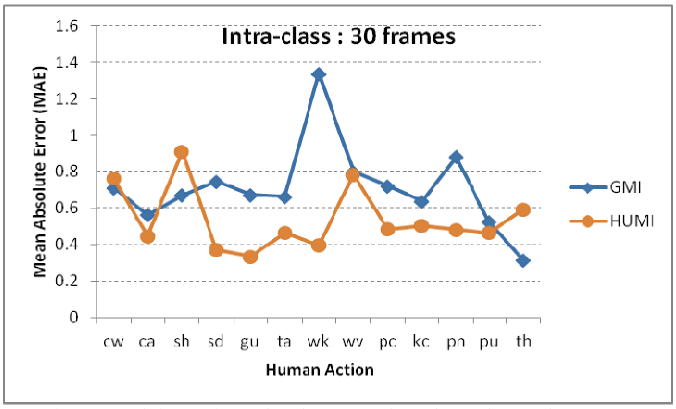

Fig. 3 Result intra-class of 13 human actions for 30 image frames

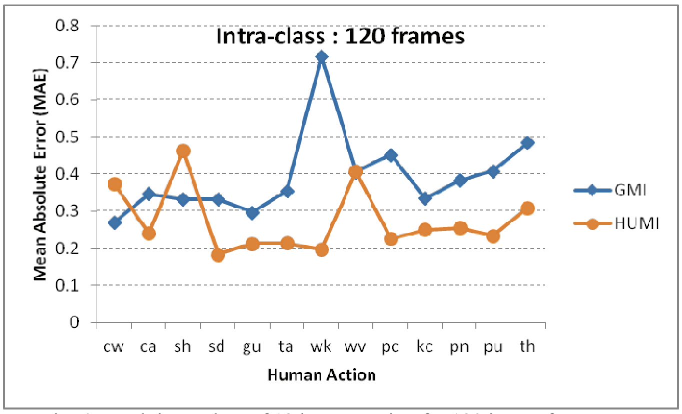

Fig. 4 Result intra-class of 13 human action for 120 image frames

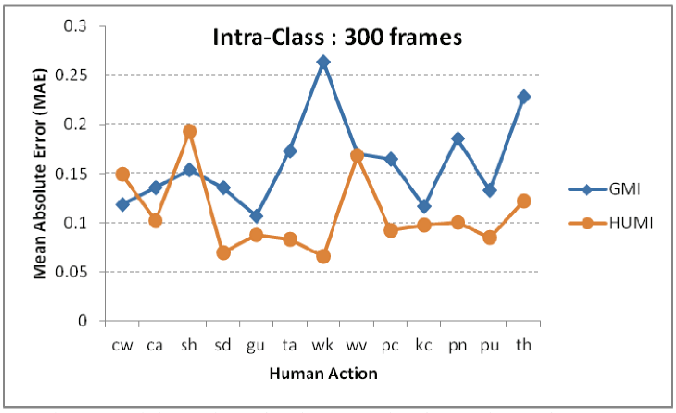

Fig. 5 Result intra-class of 13 human action for 300 image frames

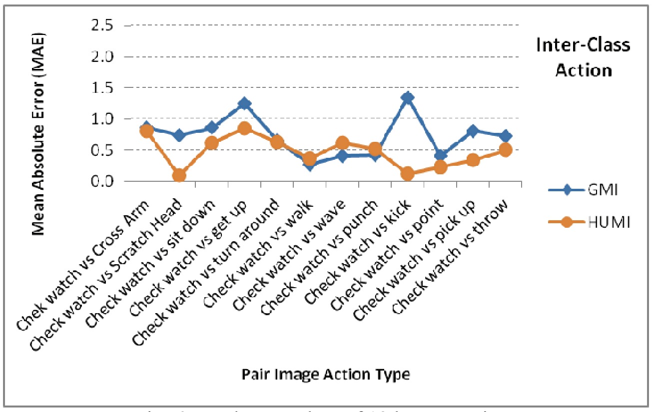

Fig. 6 Result Inter-class of 13 human action

TABLE IV. INTRA-CLASS BASED ON STANDARD DEVIATION FOR HUMAN ACTION INVARIANCENESS FOR 13 HUMAN ACTION

Action	Moment Invariant	Std 30 frames	Std 120 frames	Std 300 frames
Check watch	GMI	0.867283	0.709733	0.663218
	HUMI	**0.500383**	**0.464928**	**0.46457**
Cross Arm	GMI	0.599354	0.667874	0.680825
	HUMI	**0.420656**	**0.478322**	**0.484353**
Scratch Head	GMI	0.691785	0.691998	0.747908
	HUMI	**0.472282**	**0.466976**	**0.449432**
Sit Down	GMI	0.706606	0.699222	0.714691
	HUMI	**0.453023**	**0.452924**	**0.421827**
Get Up	GMI	0.803908	0.717972	0.740498
	HUMI	**0.338123**	**0.39949**	**0.455633**
Turn Around	GMI	0.635726	0.665968	0.714714
	HUMI	**0.519163**	**0.504384**	**0.483718**
Walk	GMI	0.715342	0.685105	0.70619
	HUMI	**0.476815**	**0.444799**	**0.442311**
Wave	GMI	1.484133	0.738212	0.733126
	HUMI	**0.569719**	**0.496344**	**0.448035**
Punch	GMI	0.766289	0.676103	0.661191
	HUMI	**0.497261**	**0.456785**	**0.475084**
Kick	GMI	0.713238	0.658099	0.702918
	HUMI	**0.481225**	**0.469002**	**0.467763**
Point	GMI	0.644184	0.68283	0.711275
	HUMI	**0.558859**	**0.491968**	**0.502599**
Pick Up	GMI	0.628074	0.751462	0.751111
	HUMI	**0.466502**	**0.443105**	**0.453954**
Throw	GMI	0.825906	0.756406	0.723947
	HUMI	**0.46864**	**0.430344**	**0.446062**

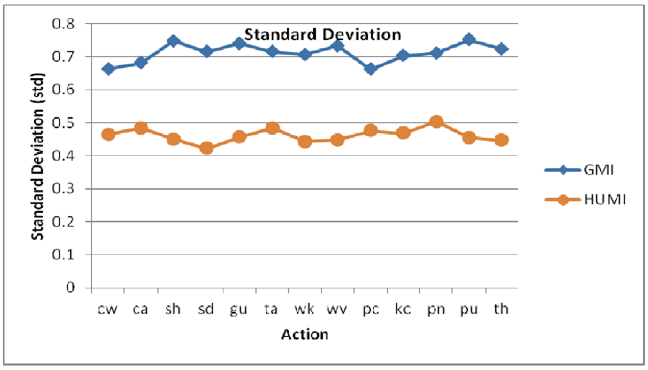

Fig. 6 Result intra-class of 13 human action based on Standard Deviation

From the experimental results obtained for intra-class analysis, it is noted that most of MAE values produced by HUMI for the 13 human actions are the smallest compared to conventional Geometical Moment Invariant (GMI) technique. Hence, HUMI is suitable for use in intra-class analysis of frame images. However, HUMI is not suitable for in inter-class analysis of the actions as it produces MAE values that are small, which are close to one another, due to the almost similar shape of the silhouettes in terms of boundary and region of the frame images. As for standard deviations analysis of all frames based on the 13 types of actions show that HUMI produces small MAE values, making it suitable for feature representation.

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B. Human Action Recognition Accuracy

The experiment has been conducted to evaluate the recognition performance by implementing several learning methods include Wavelet, Principal Component Analysis (PCA), Expectation Maximization, Normalization, Pre-Discretization (original feature) with the proposed invariant discretization (post- Discretization). The experiments have also been conducted by performing difference classifiers to evaluate the recognition performance. The classifiers used include J-48 (C 4.5) tree, Functional Tree and Best First using WEKA Toolkit. The purpose of this analysis is to identify the most significant features of each class of human action when the data have highly similar features. Fig. 7 depict the distribution of data, whereby two sets of data are divided into testing and training in human recognition task.

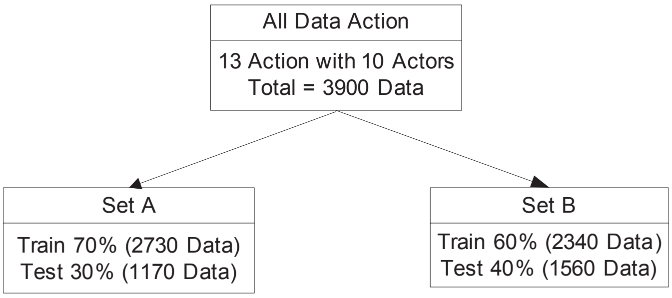


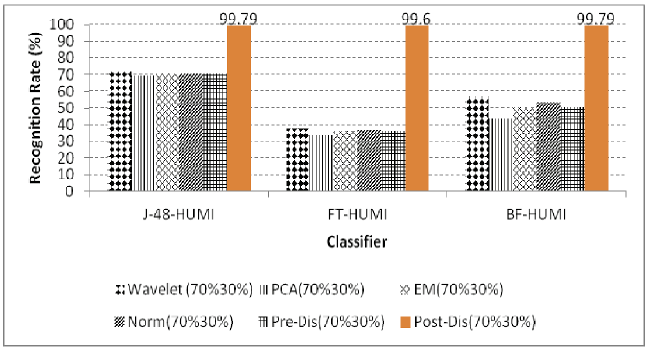
Fig..7 Data Collection for Training and Testing

Based on HUMI feature vector representation, the recognition performances of the six learning algorithms obtained from the experiments for Data Sets A and are shown in Table V, respectively. Referring to Table V, though not producing 100% recognition rate for Data Set A, however, the proposed Post-Discretization algorithm achieved a recognition rate of over 99% for J-48, FT and BF classifiers. However, the other learning methods achieve lower recognition rate, which are in the range of 69.60% to 72.05% with J-48 classifier, 33.53% to 37.65 % with FT classifier, and 43.80% to 56.69% with BF classifier. Similarly, though not producing 100% recognition rate for Data Set B, the proposed Post-Discretization algorithm achieved a recognition rate of over 99% for J-48, FT and BF classifiers. The other learning methods achieve lower recognition rate, which are 70.39% to 72.03% with J-48 classifier; 33.19% to 39.66% with FT classifier, and 28.22% to 56.88% with BF classifier.

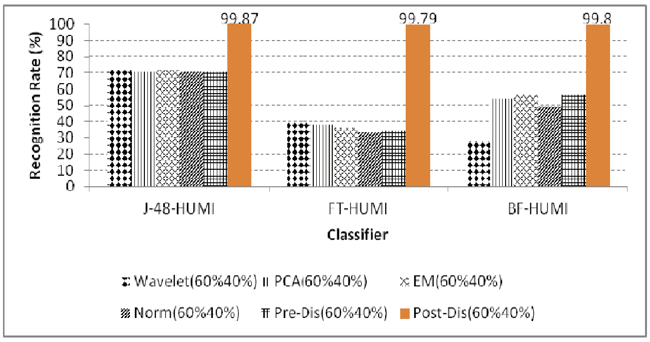
Fig. 8 shows the recognition accuracy of post- discretize data are higher compare to pre-discretize data and other learning method based on the HUMI feature vector of human action. This is due to the variance between features that have been improved by implementing discretization technique subsuquent to feature extraction with the HUMI. These features are clustered into the same cut that explicitly corresponds to the same action. The lower variation of intra-class and higher inter-class contributed to the better recognition performance.

TABLE V COMPARISON OF LEARNING METHODS WITH HUMI

Data Set	**Methods**	**Recognition Rate (%)**		
		J-48	FT	BF
Data Set A: 2730 Training Data (70%) 1170 Testing Data (30%)	Wavelet	72.05	37.65	56.69
	PCA	69.60	33.53	43.80
	EM	70.69	36.33	50.58
	Norm	70.53	36.71	53.34
	Pre-Dis	70.69	36.33	50.58
	Post-Dis	**99.79**	**99.60**	**99.79**
Data Set B: 2340 Training Data (60%) 1560 Testing Data (40%)	Wavelet	72.03	39.66	28.22
	PCA	70.67	37.87	54.12
	EM	71.94	36.12	56.88
	Norm	70.39	33.19	49.67
	Pre-Dis	70.84	34.84	56.72
	Post-Dis	**99.87**	**99.79**	**99.80**



a. Data Set A (70% Training Data, 30% Testing Data)



b. Data Set B (60% Training Data, 40% Testing Data)

Fig. 8 Recognition accuracy using HUMI

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VI. CONCLUSION

This paper proposed the human action invarianceness method based on the Higher United Moment Invariant (HUMI) in order to validate the feature representation for Human Action Recognition in Video Surveillane. The experiment of HUMI is performed to validate the human action invarianceness, and extracted features are discretized for better recognition. The results confirm that the invarianceness of human action is still preserved.

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