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Human Activity Recognition by Analysis of Skeleton Joint Position in Internet of Things (IOT) Environment

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Abstract

Objective: To provide automaticallyanalyzingand detecting human activities to provide better support in health-care sector, security purpose etc. **Method**: We have used UTKinect-Action 3D dataset containing position of 20 body joint captured by Kinect sensor. We selected two set of joints J1 and J2; after that we have formed some rules for activity classification then we have applied SVM classifier, KNN classifier using Euclidean distance and KNN classifier using minkowski distance for activity classification. **Findings**: When we have used joint set J1 we got 97.8% accuracy with SVM classifier, 98.8% accuracy with KNN classifier using Euclidean distance, and 98.9% accuracy with KNN classifier using minkowski distance and for joint set J2 we got 97.7% accuracy with SVM classifier, 98.6% accuracy with KNN classifier using Euclidean distance, and 98.7% accuracy with KNN classifier using minkowski distance. **Application/ Improvement:** we have classified four activities hand waving, standing, sitting and picking. In future more activities can also be included in this study. IOT along with this activity recognition method can be used to reduce overheads.

Keywords: Activity Recognition, IOT, Joint Set, Kinect, Skeleton

1. Introduction

Gait recognition is one kind of technology that can be used to monitor people by just observation using some sensor technology. Researchers are working on visually-based systems that use video cameras, radio waves, depth map, radar etc to analyze the movements of each body part—the knee, the foot, the shoulder, and so on. It is considered as an important aspect of computer vision due to its various applications. Gait recognition is based motion analysis of a human, animal or any other living things. Based on motion of any person we can identify the activity whatever he is doing. There are various applications of gait recognition methods like human health care, fall detection, security in surveillance applications. In health care area fall detection is one of the major application of gait recognition. Where elder person are living alone, their unconscious fall was detected using computer vision technology and immediate information can be

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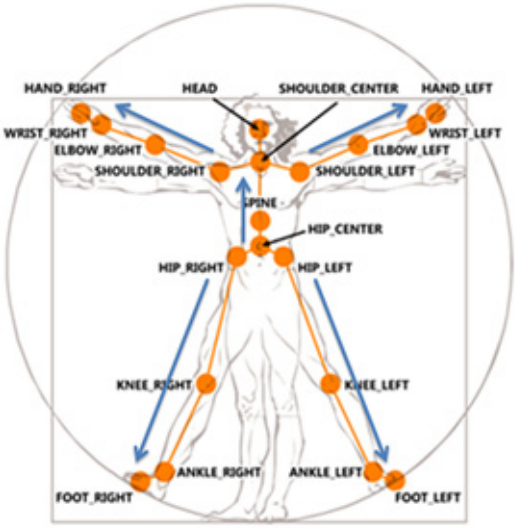


Figure 1. Body Ioint Location Extracted by Kinect[19].

given to caretaker so that immediate help will be available for him. According WHO fact sheet on falls reviewed on September 2016 Falls are the second leading cause of accidental or unintentional injury deaths worldwide. Each year an estimated 424 000 individuals die from falls globally of which over 80% are in low- and middle-income countries. For security purpose, gait of a person is recognized to identify any unwanted activity like in ATM, banks, offices etc.

Gait recognition algorithms can be broadly divided into two categories (1) Model Based and (2) Holistic approach[1]. In model based approaches parameter are extracted by analyzing gait sequences. Model-based approaches generally require rich quality gait sequence because parameters are identifies through various gait sequences. Holistic solutions operate directly on the gait sequences without assuming any specific model for the walking human.

A lot of gait recognition or posture classification work was carried out using RGB cameras[2-4]. These cameras were able to record RGB videos and posture classification was performed by using various image processing techniques. A new revolution was come into existence after innovation of Microsoft Kinect. Microsoft Kinect is a peripheral device which can be connected to computer like webcam. In addition to providing RGB image is also measure distance of pixel from camera so it makes easy background removal, blob extraction etc. The Kinect camera captures depth and color images with 30 Frames Per Second (FPS), generating a cloud of three-dimensional (3D) points from an infra-red pattern projected onto the scene. Kinect cameras also able to detect body joint locations as in Figure 1. Kinect version v.1 was able to detect 20 human body joints but Kinect V.2 was able to detect 25 Kinect body joint. The locations of these body joints are very helpful to detect human posture. Many algorithms [5-8] were also use 3D Kinect data to recognize activities.

A lot of research has been performed by analyzing body joint location extracted by Kinect depth sensor. Position of these body joint locations was used to detect human activity, fall detection etc. Microsoft Kinect return 3D location of different body joints.

3D location of body joint and joint acceleration were used to detect human posture many research works[9,10]. In a research finding a method[9] was proposed in which three

different scores were calculated to evaluate dances performance.(1) Joint Position (2) Joint velocity (3) 3D flow error. After computing 3 different scores for each of three parameters combined scores was calculated and by using this method they were able to detect the dancer performance and other method[10] also detects fall using similar approach. They calculated to velocity and acceleration of joints 21 joints, if the calculated velocity or acceleration is not high enough to detect fall, then it will check the distance between head to floor. If either of them is high, it will proceed to fall detection process. In fall detection process microphone array of Kinect will be activated to listen any voice from detected person. Then position of skeleton was computed and if the position of joints is closed to floor then fall was detected. One other related approach[11] uses position of joints relative to other joints rather than taking on individual joint location. In this method feature extraction was performed using 25 body joints and it was based on joint motion. To make joint position independent from the distance they used relative vector where start point is the coordinate of spine. They used different set of reduced joints. Classification accuracy of personal identification was 81.58%, 80.70% and 79.82% when number of joints was 10, 8 and 6 respectively. They found that classification accuracy was heavily degraded if hand or both head and shoulder were removed and classification was improved when both knees were included in the model.

Some researchers used the approach of measuring joint angles[12-14]. 3D locations of 10 joints for working with four postures sitting, lying, bending and standing were used. They used support vector machine classifier using C support vector classification. They performed the experiment in different models using absolute coordinate value of joint without scaling,; using 7 joint angle , 9 joint angle, 17 joint angle with scaling and using 7 joint angle , 9 joint angle, 17 joint angle without scaling. Higher accuracy was found standing posture classification. In other method[13] Static and dynamic features were calculated. Statics feature is Euclidean distance between two specified joints. They considered only those frames where depth was between 1.8m and 3.0m. In dynamic feature they calculate two angles a2 and a4, where a2 is angle between left knee and left ankle, a4 is angle between right knee and right ankle. They static and dynamic features were fused together using multilevel fusion. And gait recognition was achieved using nearest neighbor classification algorithm. They achieved correct classification rate (CCR) 92. In other research work[14] at first pose was estimated and different joint angles were used represent different angles.

The rapidly increasing number of interconnected devices and systems today brings concept of Internet of things. In the area of posture recognition, fall detection, face recognition etc. IOT is increasing its influence. In various research works, IOT along with fog computing was integrated with basic recognition algorithms [15-17]. In a research method[15] IoT-Based Fall Detection System with Energy Efficient Sensor Nodes were proposed. In this method they have included concept of fog computing along with internet of things. In this paper they have investigated the energy consumption of sensor nodes in an IOT based fall detection system and they presented a design on customized sensor nodes which were energy efficient. In this paper the fall detection algorithm was running on fog gateway instead of cloud. This saves the effort of sending whole data to cloud. Detection was done locally but when fall was detected that information was passed to cloud to send push notification. Other research[16] also proposed the approach to detect fall, but this method was used in WSN environment. They used wireless sensor network to sense the abnormal behavior of elderly or patients. WSN sensor node was constructed using PIR sensor and Zigbee. Discriminative spatio-temporal feature of the fall were used to analyze the difference between the fall and other normal activities. Other research work[17] presented the approach of face detection using Fog Computing in Internet of Things. In this paper they used the concept of fog computing along with IOT. At the sensor node only sensor data is collected and sent immediately to the fog unit. Fog unit was intermediate unit where algorithms of face detection, facial image preprocessing, feature extraction and face identifier generation are implemented to generate face identifier. Fog unit was connected to Management server, resolution server and information server and data centre in cloud.

2. Proposed Method

2.1 Conceptual Proposed Architecture based on Internet of Thing (IOT)

Conceptual architecture is shown in Figure 2. Conceptual architecture can be used to implement our system in IOT environment. The skeleton data collected from different Kinect sensors can be sent to cloud storage over internet. In cloud analysis of three dimensional skeleton data was performed using the method which is proposed here and recognized activity will be sent to caretaker to take appropriate action.

In the proposed method we have used relative joint position of skeleton to classify activities. As we already know that for every activity every joint has some specific relative position compared to other. we have tried this method for different set of joints to identify which of joint provide best results. The work was performed using following steps (1) Data acquisition (2) Selection of joint sets (3) Rule formation according to relation position of joints (4) classify the data using Support vector machine classifier, KNN classifier using Euclidean distance method and KNN using Minkowski Distance method.

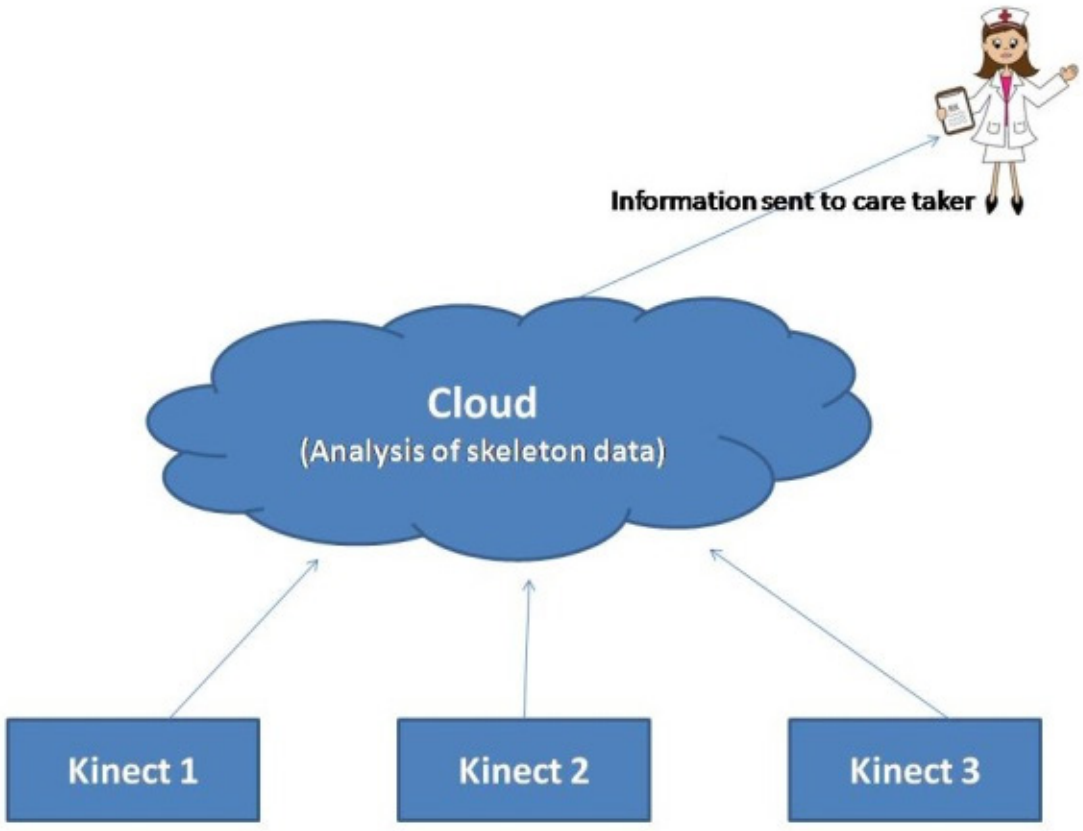


Figure 2. Conceptual Proposed Architecture.

2.1.1 Data Acquisition

In this paper we have used dataset provided by UTKinect 3D action dataset[18]. In which various activities are performed by 10 subjects twice. Location of 20 body joints is given in this dataset.

2.1.2 Selection of Joint Set

We have used y location of joint in this approach because we need to calculated only relative distance of joints from floor.We have selected two joint set J1 and J2 as shown in Figure 3.

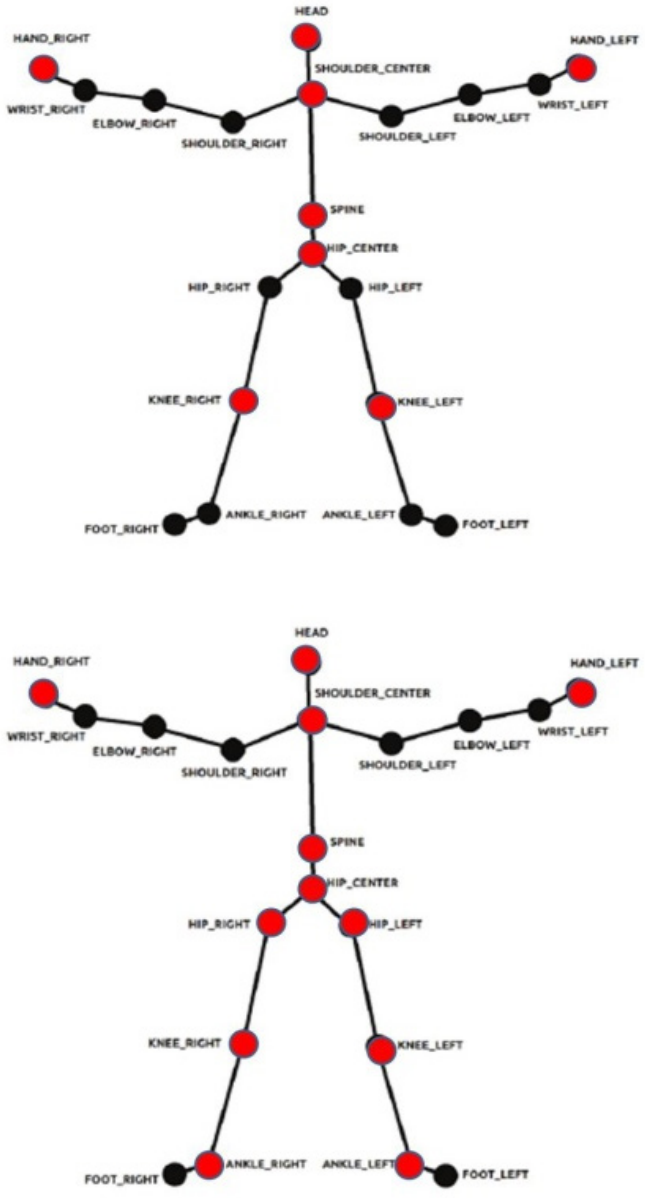


Figure 3. Joint Set J1. Joint Set J2.

J1={Head, Spine, Shoulder_center, Hand_L, Hand_R, HiP_Center, Knee_L, Knee_R)

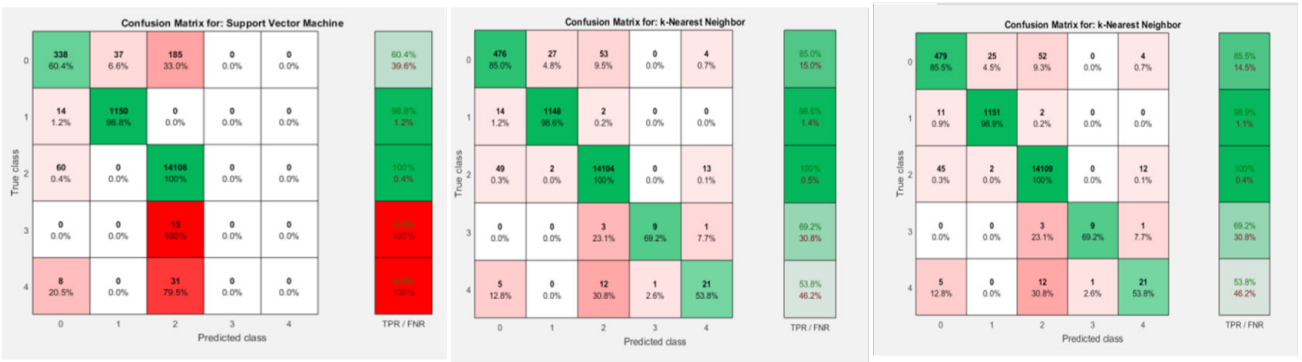
Joint set J2={Head, Spine, Shoulder_Center, Hip_l, Hip_R,Hip_Center, Knee_L, Knee_R, Foot_L, Foot_R, Hand_L, Hand_R)

2.1.3 Rule Formation

We have considered four activities here like standing, sitting, picking, hand waving. Every joint location has relative position with respect to other joint. So made some

Table 1. Rules which are used to classify activities

Activity	Rules for relative position of Joints
Hand Waving	Hand_L>Shoulder_center Hand_R>Shoulder_center Head>shoulder_center>spine>Knee_l & Knee_R
Standing	Head>shoulder_center>spine>Knee_l & Knee_R
Picking	Hand_l<Knee_l Hand_R<Knee_R
Sitting	Hip_center-Knee_l<0.40 Hip_center-Knee_R<0.40



Using SVM classifier | KNN classifier using Euclidean distance | KNN classifier using Minkowski distance

Figure 4. Confusion Matrix for Joint Set J1.

Using SVM classifier | KNN classifier using Euclidean distance | KNN classifier using Minkowski distance

Figure 5. Confusion Matrix for Joint Set J2.

rules which predict the activity by using analyzing relative location of joint. Table 1 presents the rules which are used to classify activities.

2.1.4 Classification

After calculating relative joint location we have identify activity then we have applied three classifiers SVM classifier, KNN classifier using Euclidean distance and KNN classifier using minkowski distance to get accuracy of our method.After applying these classification techniques we got confusion matrix as in Figure 4 for joint set J1 and Figure 5 for joint set J2

3. Results And Discussion

Table 2 reveals that when we use joint set J1 we get 97.8% accuracy with SVM classifier, 98.8% accuracy with KNN classifier using Euclidean distance, and 98.9% accuracy with KNN classifier using minkowski distance. When we used extended set of joint J2 we get 97.7% accuracy with

Table 2. Classifiers and the accuracy

Joint set	Accuracy		
	SVM Classifier	KNN classifier using Euclidean distance	KNN classifier using minkowski distance
J1	97.8%	98.8%	98.9%
J2	97.7%	98.6%	98.7%

SVM classifier, 98.6% accuracy with KNN classifier using Euclidean distance, and 98.7% accuracy with KNN classifier using minkowski distance. We found that when we used J1 joint set we get better results for classifying activities.

4. Results

We have analyzed relative position of joint to classify human activities and have classified as standing, sitting, picking and waving. We formed two set of jointsJ1 and J2. After rule formation, we have applied SVM and KNN classifiers to the data. We found best results with J1 set of joints and KNN classifier using minkowski distance method. In future, more action can be included for classification along with practical implementation of this concept with IOT.

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