Gait and Full Body Movement Dataset of Autistic Children Classified by Rough Set Classifier

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Abstract: Gait and body movement are a window to human brain which make these activities unique for each person. These activities are used to diagnose some disorders related to parts of brain which causes have not been known such as Autism Disorders (AD). The traditional diagnostic methods of AD are time-consuming and highly dependent on clinician’s judgment which is based on behaviour assessment. This approach leads to subjective interpretations that differ from doctor to another and affect by strengths and weaknesses of patient. Therefore this paper aims to diagnosis of AD based on gait and body movement analysis. At first, Kinect v2 uses to create a 3D dataset, which includes three dimensional joints positions, joints trajectories video, skeleton movement video captured by Kinect v2, and color videos captured by Samsung Note 9 camera. This paper also aims to classify children with autism from normal children by proposed system based on four stages: Augmentation of the database by using seven transformations to deal with small number of autism cases; Extracting features that we think play an important role in classification; Reducing data dimensions using Principal Component Analysis; using Rough Set to classify dataset. Results show that classification is 92% after augmentation.

1. Introduction

Understanding the causes of Autism Disorders (AD) has always been the dream of doctors and researchers. AD is a pervasive neurodevelopmental disorder diagnose by the age of two years or sometimes even earlier and characterize by a triad of impairments: social communication problems, difficulties with reciprocal social interactions, and unusual patterns of repetitive behavior [1]. Unfortunately, no medications can cure AD or treat its core symptoms but can help some people affected feel better, while the early professional care can make a big difference in preparing these autistic kids for safety life.

Possible signs that could identify AD are unusual behavior patterns [4], frequent body movements, and purposeless motor signs which referred to as stemming or stereotypy [2]. Stimming of children with AD has been gaining greater attention in recent years. However, little studied why these children exhibit differences in their movement and what is the relationship between these movements, which may lead to understand the underlying etiology of the disorders. Stimming can be studied from videos captured in two environment types. In uncontrolled environments, when the children are performing their daily activities, some self-stimulatory behaviors can be studied by
automatically analyzing the captured videos. On the other hand, controlled environments can also
use where a therapist exercises a defined protocol of play action with the child to elicit higher-level
behaviors. Children's behaviors in both scenarios analyzing are equally important for early
intervention and diagnosis.

In the same context, the second version of the Microsoft Kinect is one of the 3D cameras that
could be used in clinical applications and captures children's behavior in both environments. It
uses time-of-flight (ToF) to estimate the distance to an object surface using active light pulses
from a single camera based on time and speed that light has taken to reflect from the object. It
contains a color camera with resolution (1920 * 1080), a depth camera with resolution (512 * 424),
and a microphone multi-vector [3], in addition to 30 frames per second for recorded color video
and tracked skeleton. Recently, it is widely used because of its cheap price, high accuracy, small
size, high speed, ease of capturing motion based on a depth camera without the need for wearable
devices.

This research aims to provide a new publicly available three-dimensional dataset, Self-Stimulatory
Behavior Dataset (SSBD) for autistic children and normal children to study the behaviors based on
the skeleton data extracted by the Kinect v2 at the time that children walk towards the camera
(controlled environment). This research proposes 1) Three-dimensional dataset with 25 body joints
positions and 16 angles between joints captured by Kinect v2 in a controlled environment, 2) Dataset
contains color videos, skeleton tracking videos and trajectory tracking videos for 109 children, 3) Augmentation approach to increase the diversity of data available for training models,
4) Extracting about 1259 features for body movement. 5) Using Principal Component Analysis
(PCA) to dimension reduction and 6) Using Rough set to classify data.

The rest of this paper is organized as the following: Section 2 presents materials and methods
which include data collection procedures and environment, data preprocessing, dataset
augmentation approach, features extraction, dimension reduction, and classification approach.
Section 3 presents the structure of the of dataset.

2. Materials and Methods

To generate 3D dataset and classified data, body joints positions have been collected during
walking of normal children and children with AD as shown Figure 1.

![Figure 1](image-url)

Figure 1. The proposed system.
2.1 Participants
Fifty-nine children with AD have been collected from seven AD childcare centers and fifty normal children in Iraq are included in dataset. The degree of AD was severe for nine children with a lack of response and great dispersion. In this case, we included color video for children for scientific benefit. While other fifty children with AD and fifty normal children are participated in the study. All participants were free of any lower-extremity injury before the data were collected, and all were free of any neurologic disorders or diseases that could interfere with their body movement and gait patterns except AD. Before the collection of data, all parents of the participating children in this research have signed the informed consent of the world health organization. Demographic data of the two groups are shown in Table 1:

| Parameter    | Autism       | Normal       |
|--------------|--------------|--------------|
| Age (years)  | 4-12 years   | 6-11 years   |
| Height (cm)  | 90-130 cm    | 100 -143 cm  |
| Weight (kg)  | 20-58 kg     | 23-55 kg     |

2.2 Environmental setup and Procedure:
To ensure the best possible achievement, the temperature was measured periodically using mercury thermometer and it ranges from 20°C to 22°C. The ventilation was also good, which prevented the overheating of the camera. The camera placed away from direct sunlight and to ensure good lighting, the brightness measured frequently using the Lux Light Meter application on Samsung galaxy note 9 and it in range from 76 Lux to 87 Lux. The Kinect camera placed at a height of 0.75m and the recording was started 20 minutes after the camera was turned on. Children were asked to walk along a line, at normal speed, towards Kinect camera. The cameras recorded color video and tracked skeleton for 10 gait cycles then we choose one suitable gait. Each time the participant walks about two gait cycles in the range of 1.5 to 4 meters in front of the camera. Then we extract one gait cycle to use in the following stages. The height of camera and distances between children and camera were chosen according to recommendations for getting the best data quality as shown in Figure 2.

![Figure 2. Environmental setup of Kinect v2.](image-url)
2.3 Data Records

Two cameras have been used:

1- Kinect v2 which recorded position of each joint as coordinates (x, y, z): Each of these joints is recorded in specific range measured in meter; x ranging from -6 (max distance to right) to +6 (max distance to left), y ranging from -5 (max distance to bottom) to +5 (max distance to top), and z ranging from 0 (on surface of camera) to 8 (max depth from camera). We used C# 5.0 in visual studio 2012 connected with Kinect camera in order to extract body joints and angles between joints which save as .csv file and draw body joints (skeleton) and trajectory of each joint. Figure 3 shows joints and angles which extracted by Kinect v2:

2- Samsung note 9 rear camera with digital 0.45X professional wide angle lens (58 MM): This camera recorded Full HD video with 60 fps and resolution 1920*1080. (12MP, f/1.5), in addition to wide angle lens which positioned on rear note 9 camera to get a wide view.

In the same context, we encountered three limitations with Kinect v2:

1- Self-occlusion in capturing lateral body movement: This occurred when part of a body hidden by another, as shown in Figure 4. This limitation has been overridden by adopting the front walk toward the camera.

2- The limited range of skeletons tracking: Kinect v2 tracking skeleton in the range [1.5m -4m] from a camera which in some cases prevented the completion of two gait cycles, this limitation has been overcome by extracted one gait cycle.

3- Frame rate of skeleton data reduces when recording color frames to 15 fps rather than 30 fps. To avoid this problem, Kinect camera was used to tracking skeleton with 30 fps and used Samsung galaxy note 9 to record color video with 60 fps.

| no. | joint | no. | joint | no. | joint | no. | joint |
|-----|-------|-----|-------|-----|-------|-----|-------|
| 1   | Head  | 5   | Wrist Left | 15  | HandTip Right | 22 | Ankle Left |
| 2   | Neck  | 9   | Wrist Right | 16  | Spine Mat | 23 | Ankle Right |
| 3   | Spine Shoulder | 10 | Thumb Left | 17  | Spine Base | 34 | Foot Left |
| 4   | Shoulder Left | 11  | Thumb Right | 18  | Hip Left | 25 | Foot Right |
| 5   | Shoulder Right | 12  | Hand Left | 19  | Hip Right |
| 6   | Elbow Left | 13  | Hand Right | 20  | Knees Left |
| 7   | Elbow Right | 14  | Hand Tip Left | 21  | Knees Right |

Figure 3. Joints and angles recorded by Kinect v2.
2.4 Data pre-processing
The gait cycle has been processed as the following:

2.4.1 Extracting one gait cycle
Each child walked in front of cameras for 2.5m for ten times where Kinect v2 recorded joints movement features. One of these features is the distance between feet which used to extract features of one gait cycle. This feature is rising and falling two times in a single gait cycle as shown in Figure 5.

2.4.2 Replacing of missing data
Choosing the optimal method to deal with missing values is always based on trial and error. In general, there are three methods: eliminate missing data, ignore the missing value during analysis, and replace missing value by another value. In eliminate missing data and ignore the missing value during analysis approaches, the sample size of data is reduced. In this paper, since we have data of one gait cycle then these approaches are excluded. On the other hand, replace missing value could be a good approach (except for replacing by mean which sometimes affected by outliers). This research-based on mice function in R language version 3.2.6 to replace missing values based on the impulse of many times. At first, the mice function detects the variables which have missing values, then missing values are replaced by Predictive Mean Matching (PMM) [5,
In this method, a small set of candidates (usually 3, 5, or 10 candidates) has been formed for each missing entry where all candidates in the set have predicted values closest to the predicted value for the missing entry. Then one of the candidates is randomly selected and replace the missing value.

2.4.3 Face detection and blurring
Faces have been detected by two methods: Haar Cascades and Multi-Task Cascaded Convolutional Neural Network. The first method quickly detected the face, but in some cases such as non-frontal face detection and occlusion, Haar Cascades fails in detected faces. On the other hand, MTCNN is powerful technique for face detection and face alignment but it is slower than the Haar method. In this research, Haar Cascades and MTCNN are used together to combine speed and accuracy of the face detection process. At first, if Haar Cascades fails in detecting faces then image passed to MTCNN to detected faces. For more processing speed, the sizes of images are reduced with twenty percent before a feed to MTCNN. Then, Gaussian blur file has been used to blurring detected face.

2.5 Augmentation Approach
The augmentation approach is shown below:

2.5.1 Dataset Augmentation
Dataset Augmentation [12] is done by applying a set of transformations to the original dataset to increase the diversity of data available for training models; enhance size and quality of dataset and avoid overfitting with taking into account preserving the label of data, these transformations have described below and shown in Figure 6:

1-Jittering: Simulating random sensor noise increases the robustness of the training data against various types of sensors and their multiplicative and additive noises. Gaussian noise is used in this research to add jittering to raw training data.

2-Scaling: Scaling is another technique adopted in data augmentation which changes the magnitude of the raw data but preserves the labels.

3-Translation: Shifting images left, right can be a very useful transformation to avoid positional bias in the data.

4-Flipping: Horizontal axis flipping is much more common than flipping the vertical axis.

5-Slicing: It is a subsampling method to randomly extract continuous slices from the original time series.
Figure 6. Results of augmentation dataset.

Before classifying data, the augmentation dataset is shuffled and divided into training (seventy percent) and testing set (thirty percent). Augmentation dataset has shuffled block by block where each block contains instance and its augmentation to ensure no leakage of augmentation instances to the testing set after dividing dataset. On the other hand, augmentation instances have been used only in training set while testing set contains the original instance since the goal of data augmentation is increased the diversity of data available for training models.

2.5.2 Three-dimensional projection
In general, projection is the representation of points in the coordination system of dimension N into a coordination system with less dimension [7]. There are two main graphical projection categories: parallel projection and perspective projection. Parallel projection is a projection of an object in three-dimensional space onto the projection plane where projection lines are parallel to each other, while perspective projection occurs when projector lines converge at the center of projection (Vanishing point), which results in many visual effects of an object. Perspective projection depends on the relative position of the eye and the view plane and considered more realistic than a parallel projection since it nearly resembles human vision and photography [7]. Kinect v2 software development kit provided build-in MapCameraPointsToColorSpace function which for the 3D projection of joints recorded directly from camera while skeleton tracking. In this paper, for the purpose of 3D projection of joints recorded at different times and resulting from augmentation stage, there was a need to build a special projection matrix [8,9] as shown in Equation 1:

1- Representing 3D joints in homogeneous coordinate [10]: This step aims to represent 3D joints in projective space by producing N+1 numbers form N-coordinates. In this paper, we add a variable w into existing coordinates to represent each joints position (x, y, z) as (x, y, z, w).
Determining affine matrix: This matrix used to correct geometric distortions that result from non-ideal angles of the camera.

Calculating the intrinsic matrix of Kinect v2: It calculated based on information captured by build-in GetDepthCameraIntrinsics function of Kinect v2:

\[
\begin{bmatrix}
X \\
Y \\
1
\end{bmatrix}
= \begin{bmatrix}
fx * sx & 0 & cx \\
0 & fy * sy & cy \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
r_{11} & r_{12} & r_{13} & t_1 \\
r_{21} & r_{22} & r_{23} & t_2 \\
r_{31} & r_{32} & r_{33} & t_3 \\
0 & 0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
x \\
y \\
z
\end{bmatrix}
\]

Where \(fx\) and \(fy\) are focal length of the camera; \(sx\) and \(sy\) are scale factor; \(cx\) and \(cy\) are the principle point of camera and \(r\)’s are rotation factors. To get projection results closed as much as possible to Kinect v2 mapping, GetDepthCameraIntrinsics function provides focal length (both equal 366.8) and principle point (\(cx=260.3, cy = 208\)). We also used scale factors (\(sx, sy\)) equal to 2 and multiply principle points by 3 and 2.2, respectively. On the other hand, rotation factors \(r_{11}, r_{33}\) equal -1 and \(r_{22}\) equal 1 to rotate joints with 180 degrees around y coordination. Figure 7 shows skeleton results from two approaches:

![Figure 7](image)

2.6 Feature Extraction

It is a method of creating an important point, distance, angles, range of movement, or any features or combination of features that may contribute to the distinction of the movement of persons. It is very complex since gait patterns categorized by time dependence, high dimensionality, and nonlinearities [11]. From the gathered data described above, we extracted difference features and gather them into four groups:

i. The distance between the joints: The distance has been measured using Euclidean distance between 3D joints positions where:

\[
d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2 + (z_2 - z_1)^2}
\]

ii. The distance between some joints and the ground: It gives important information in classification gait of children with AD and normal children gait, where:

- Head to ground distance distinguishes weak visual communication in children with AD
- SpineBase to ground distance distinguishes jumping and bounce
- Hand tip to ground distance distinguishes flutter, put hands on ear and fingertip in front of eyes
Ankle to ground distance distinguishes toe walking and jump
With Kinect v2, floorClipPlane property calculates joint to ground distance by getting 4 float-point value (A, B, C) for orientation of the plane in the 3D space and W for the distance between the plane and the origin of the coordinate system. Then distance can calculate by:

\[ d = \frac{Ax+By+Cz+W}{\sqrt{A^2+B^2+C^2}} \]  

(3)

iii. The range of motion for each joint coordination which determines how far joints can move in different directions and distinguishes gross gait coordination. range of motion of each joint calculates by:

\[ \text{ROM (joint.N)} = \max (\text{joint.N}) - \min (\text{joint.N}) \]  

(4)

Where N may be x or y

iv. Other attributes:

- The body is divided into upper and lower half according to y coordinates of SpineBase and determines the position of hand tip based on it. This can determine any abnormal movement of the hand.
- Step length, step width, and the distance between feet and stride length, as bellow:
  
  \[ \text{Step length} = \text{Joint.z(t(1))} - \text{Joint.z(t(2))} \]  
  
  (5)
  
  \[ \text{Step width} = |\text{Joint.x(t(2))}-\text{Joint.x(t(1))}| \]  
  
  (6)
  
  \[ \text{Stride length} = \text{Joint.z(t(1))} - \text{Joint.z(t(n))} \]  
  
  (7)

- Gait cycle time, stand time and swing time

After calculating statistical measures (mean, variance, standard deviation) of all features, we get about 1259 features which feed to dimension reduction technique. All extracted features have shown in Figure 8.

2.7 Dimension reduction
Principal Component Analysis (PCA) aims to reduce amount of computation needed through focusing on the major differences in features, selecting few of these features and making new transforming of data based on selected sample. All this is done through analyzing the relationship among a set of connected instances and reducing the dimensions to produce a new dataset with a lesser number of dimensions. In this paper, all features have been fed into PCA and as the result, we get thirty-one features, only the top eleven features have been selected based on its standard division and passed to Rough set classifier.
Figure 8. Extracted features, (a) distance between joints, (b) Distance between head, spine base, Hand tip (left and right), Ankle (left and right), (c) Range of movement joint on x and y coordination, (d) step length, step width and parts of body.

2.8 Rough set

In the early 1980s, Zdzislaw Pawlak presented Rough Set Theory (RST) [13] as a mathematical approach to data mining and intelligent data analysis as it discovered hidden patterns in data by using mathematical tools. It removes redundant data, determines data dependency, provides an approach to dealing with missing data, and others. Also, it can be used for feature extraction, data reduction, feature selection, pattern extraction, and decision rule generation, etc. [14].

Some basic concepts [14] on rough set theory are reviewed as follows:

1-Information system: A decision table or information system is \( T = (U, Q, D, V, f) \), where the set of decision-making attributes are symbolized as \( D \), set of examples is called the universe and symbolized as \( U \), set of conditional attributes symbolized as \( Q \), \( V = U \times Q \times V_q \) and \( V_q \) is a set of all possible values of attributes, and \( f: U \times Q \rightarrow V \) is a function of information.

2-Indiscernibility Relation: Given a subset of attribute set \( B \subseteq Q \), an indiscernible relation \( \text{ind}(B) \) on the universe \( U \) can be defined as follows:

\[
\text{ind}(B) = \{(x, y) | (x, y) \in U^2, \forall b \in B (b(x) = b(y))\}
\] (8)

3-Approximation: The rough set theory depends on two basics concepts, namely the lower and the upper approximation as shown in Figure 2.9. Let \( X \) be a subset of \( U (X \subseteq U) \). Let \( P \) is a subset of \( B \). For a set of attribute \( P \):

- The lower approximation of \( X \) is the collection of objects that certain classified as \( X \), using \( P \):
  \[
P^X = \{x \in U | [x]_P \subseteq X\}
  \] (9)

- The upper approximation of a set \( X \) is the collection of objects that possibly classified as \( X \), using \( P \):
  \[
  \bar{P}X = \{x \in U | [x]_P \cap X \neq \emptyset\}
  \] (10)

- Let \( P, Q \subseteq A \) be equivalence relations over \( U \), then the positive and boundary regions can be defined as follows:
  - The positive region of \( X \), using \( B \) is:
\[ \text{POS}_p(Q) = \overline{\text{PX}} \quad \ldots \quad (11) \]

- The negative region of \( X \) using \( B \) is:
  \[ \text{Neg}_p(Q) = U - \overline{\text{PX}} \quad \ldots \quad (12) \]

- The boundary region is the difference between the upper approximation and lower approximation.
  \[ BND_p(Q) = \overline{\text{PX}} - \text{PX} \quad \ldots \quad (13) \]

4- Quality and accuracy of the approximation (Gamma) of the family \( F \). Gamma determines whether there are enough cases or conditional attributes (or both) to forecast the value of a decision. It calculates based on Equation 14.:

\[ k = \gamma_c(F) = \frac{|\text{POS}_p(F)|}{|U|} \quad \ldots \quad (14) \]

Figure 9: A Rough Set in Rough Approximation Space [14]

2.9 Classification evaluation

Different measures are calculated to evaluate the classifier as shown below:

1- Confusion matrix: It is calculated for classifier when deal with dataset before and after augmentation as shown in Table 2:

| Table 2: confusion matrix before dataset augmentation and after dataset augmentation |
|---|---|---|---|
| Before augmentation | After augmentation |
| | Predicted | | Predicted |
| | Autism | Normal | Autism | Normal |
| Actual | Autism | 7 | 9 | Autism | 12 | 2 |
| | Normal | 1 | 8 | Normal | 0 | 11 |
3- Other evaluation measures: Specificity, Accuracy, Sensitivity, and Error rate are calculated for classifier when dealing with dataset before and after augmentation as shown in Table 3:

**Table 3:** Evaluation measures of classifier before and after dataset augmentation  
| The measure   | Before augmentation | After augmentation |
|---------------|---------------------|--------------------|
| Accuracy      | 60%                 | 92%                |
| Error rate    | 40%                 | 8%                 |
| Sensitivity   | 88%                 | 100%               |
| Specificity   | 43%                 | 85%                |

4- The plot of learning curves: Curves of training and validation error for dataset before and after augmentation are calculated for classifier as shown in the Figure 10 below:

**Figure 10:** a) Learning curve before augmentation dataset, b) Learning curve after augmentation dataset.

Figures above shows that the learning curve of dataset after augmentation is characterized by the following:
1- Learning curves are not a flat line from the beginning to the end of the plot. Also, these curves are not continuously decreased to the end of plot which means the model is not under-fitting.
2- Training curve is not continuously decreased to the end of the plot and validation curve is not decreased to point and begin increased to the end of plot which means the model is not over-fitting.
3- The learning gap (the gap between training and validation error) is reduced. Training and validation errors are stable at the end of the plot which means that model is good.
3. **Data set structure** (https://doi.org/10.5061/dryad.s7h44j150)

Each of the 109 children has a folder as shown in figure 11:

![Dataset structure diagram](https://example.com/dataset.structure.png)

**Figure 11:** Dataset structure.

4. **Conclusion**

The primary goal of this paper is to create a 3D dataset for the gait of children with AD and classify them from normal children based on gait analysis and body movement analysis. After obtaining approval from the parents, the children were asked to walk toward the camera, which tracked the movement of the joints and captured the angles between the joints. We extracted a single gait cycle based on the distance between the feet and then extracted features that we think are important for classification. Given that the number of cases is relatively few, a dataset augmentation based on seven transformations saves the label of movement, increases the cases in the dataset, and improves classification model. A dimension reduction approach was used to make feature transformations and to produce fewer features with better classification accuracy. In the end, we used Rough set for the classification task. Results show that classification accuracy before augmentation is 60% while classification accuracy after augmentation is 92%.

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