Predicting Pedestrian Irregular Behavior Using Talchum Data

Big Data_2024_2nd_Semester

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Contents

01. Project Overview

- Project Background and Motivation
- Problem Definition and Objectives

Project Background and motivation

Pedestrian

70%

(Basic fault)

Driver

30%

"Considering pedestrians' vulnerability and vehicles' duty to stop."

✔ In **South Korea**, pedestrians account for **38.9%** of all traffic fatalities, double the OECD average of 19.3% (Japan also 36.6%)

✔ In October 2024, **New York City** repealed its jaywalking ban, effectively legalizing jaywalking → **increase in pedestrian accidents**

✔ The **global autonomous vehicle market** is expected to grow from $41.1 billion in 2024 to **$114.5 billion by 2029**, with a 22.75% CAGR

출처) 과실비율정보포털, Morder Intelligence

Problem Definition & Objective

Predicting Pedestrian Irregular Behavior Using Talchum Data

Problem Definition

High pedestrian accident rates

Policy changes and global trends

Growth of the autonomous vehicle market

Lack of technology for detecting irregular pedestrian behavior

Potential of Talchum data

Objectives

Refining Talchum data with key patterns

Enhancing detection of irregular pedestrian behavior

Pedestrian detection using YOLO and Mask R-CNN

02. Data Analysis

- Data collection
- Data analysis

Collection of Data

#문화

NEW **탈춤 동작 데이터**

분야 문화관광 유형 이미지

구축년도 : 2023 갱신년월 : 2024-12 조회수 : 1,844 다운로드 : 29 용량 : 5.26 TB

다운로드 샘플 데이터 관심데이터 등록 4

메타데이터 구조표

데이터 영역	문화관광	**데이터 유형**	이미지
데이터 형식	JPG	**데이터 출처**	자체 수집
라벨링 유형	바운딩박스(이미지/동영상)/키포인트(이미지/동영상)	**라벨링 형식**	JSON
데이터 활용 서비스	탈춤의 원격비대면 교습 및 심사, 자세교정 등 인터랙티브 서비스	**데이터 구축년도/ 데이터 구축량**	2023년/원천데이터 126,728장, 라벨링 데이터 126,728개

1. Collection of **AIHub** Talchum Motion and Labeling Data.
2. Class IDs: HC (Master), MC (Skilled), LC (Unskilled)
3. **Selected Class:** MC (Skilled)
    a. 41,507/126,728 **(32.75%)**
    b. **43.91GB (raw), 59.97MB (labeled)**

- *HC (Master) motions are overly precise and structured, while LC (Unskilled) lacks consistency. MC (Skilled) is considered to more closely resemble real pedestrian behavior pattern.*

출처) AI Hub *탈춤 동작 데이터*

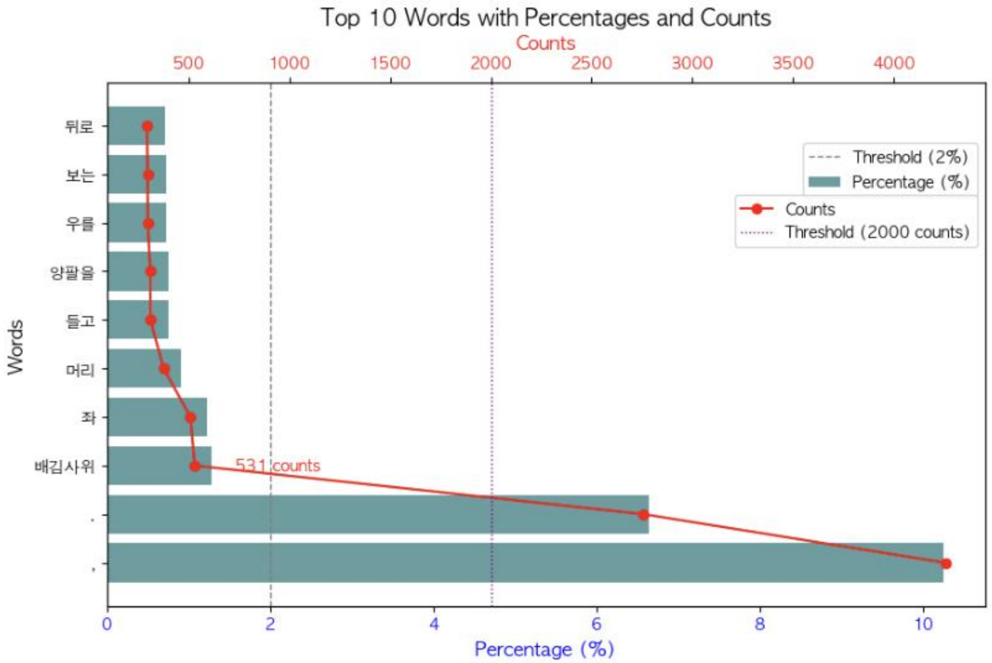
Data Analysis 1

02

1. **Word Cloud**
    a. Frequency
        i. 배김사위, 좌, 머리, 들고 etc.
    b. **Unexpected pedestrian behavior on the road**
        i. **뛰다(Run)**: Reflects sudden dashes into the road, similar to jaywalking.
        ii. **돌다**, **돌림(Turn)**: Indicates abrupt changes in direction.
        iii. **움직임(Movement)**: Covers irregular behaviors.
        iv. **뿌리다(Scatter)**: Represents unexpected hand or arm movements.

💡 ***[Insight]*** *Irregular motions in Talchum data (e.g., Run, Turn, Scatter) are predicted to be effective in detecting unexpected pedestrian behaviors, such as jaywalking, which involve irregular patterns.*

Data Analysis 2



2. **Top 10 Words**
   a. 배김사위, 좌, 머리, 들고, 양팔을, 우를, 보는 …
   b. Check the **"Talchum_info"** attribute in the metadata.

"Talchum_info": {
…
"Talchum_important": "배김사위, 앞배김새, 뒷배김새, 겨드랑배김새 동작이 강하여 뛰어서 땅을 내려 누르듯이 힘차게 착지하는 동작."}

   c. 배김사위(Baegim-sawi)
      i. 531 appears.
      ii. A leaping move with one leg stomping down and the other stretched back.

💡 ***[Insight]*** *Irregular lower-body movements like Baegim-sawi in Korean mask dance may provide useful data for learning and detecting sudden pedestrian behavior.*

출처) 국립국악원 공식 블로그

Data Analysis 3

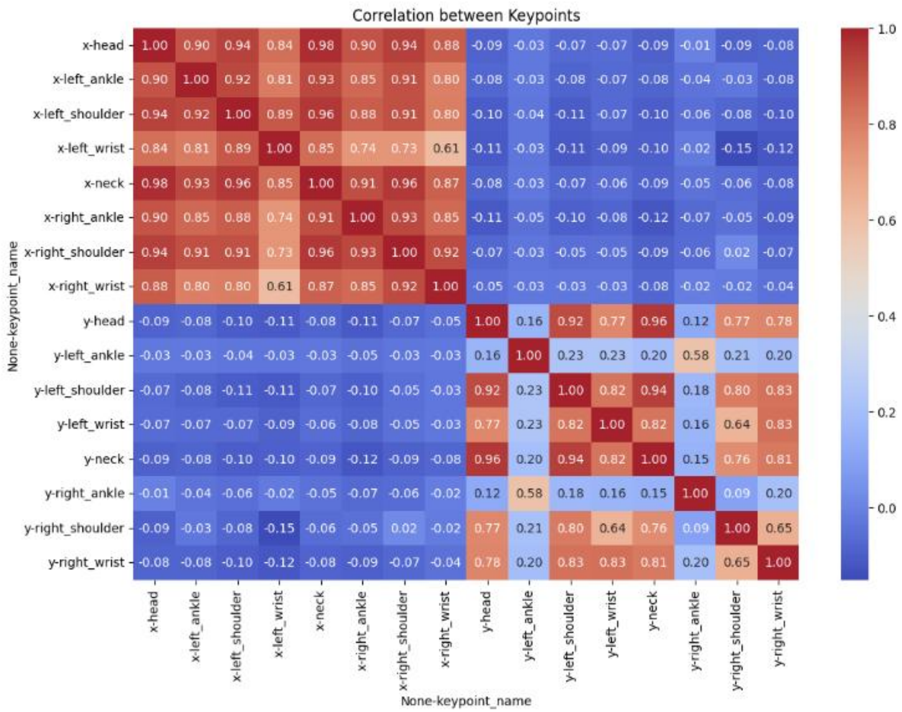
1. **Data Preparation and Cleaning**
   a. 11.2% of the (x, y) coordinate data were missing and were filled using linear interpolation.
   b. **Extracted as 'filtered_keypoints.csv'.**

2. **EDA**
   a. Keypoint Analysis for Anomalous Behavior Detection.
      i. **Hands (left_wrist, right_wrist)**: sudden shaking and irregular movement patterns.
      ii. **Shoulders (left_shoulder, right_shoulder)**: represent the overall movement of the upper body.
      iii. **Knees (left_knee, right_knee) and Ankles (left_ankle, right_ankle)**: indicators of direction change and rapid movement.
   b. **Extracted as 'filtered_keypoints_interpolated.csv'.**
   c. Correlation Analysis between Keypoints and Height
      i. The correlation between the dancer's height and the (x, y) coordinates was very low.
      ii. Since the coordinate data represents relative positions within each frame, it shows low direct correlation with physical attributes like height.
      (See: step2_EDA_correlation.ipynb for details)


```json
{
  "level_id": "MC1",
  "keypoint": [
    {
      "keypoint_no": "1",
      "keypoint_name": "head",
      "x": 2046.7654175779205,
      "y": 1129.0463601653646
    },
    {
      "keypoint_no": "2",
      "keypoint_name": "neck",
      "x": null,
      "y": null
    },
    {
      "keypoint_no": "3",
      "keypoint_name": "left_handEE",
      "x": 2039.2211542706978,
      "y": 1192.3866122788147
    },
```

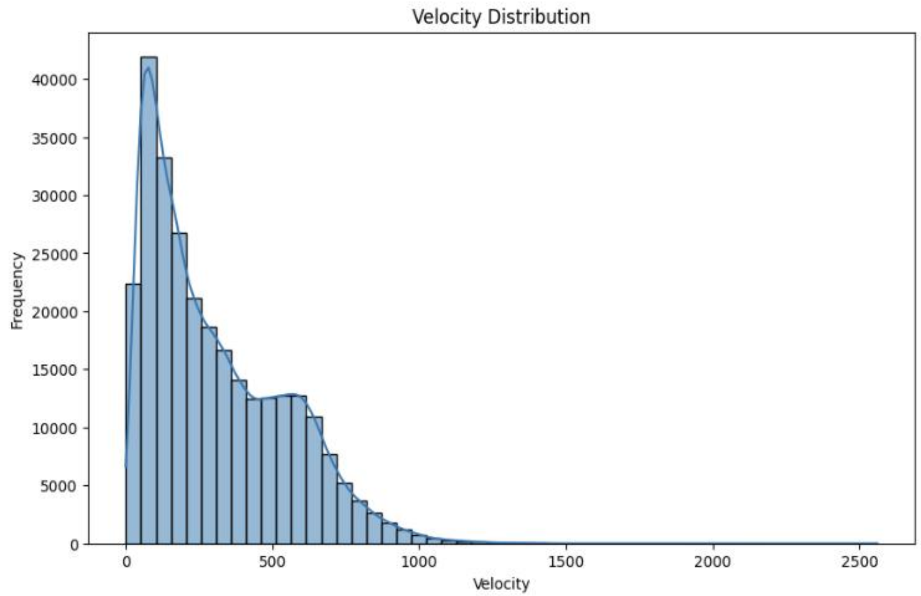
Data Analysis 3.1

3. **Correlation Between Keypoints**
   a. Understanding the physical characteristics of pedestrian behavior → Separation of upper and lower body movements
   b. Extracted as Upper Body Correlation, Lower Body Correlation
   c. **Upper Body**
      i. left_shoulder ↔ right_shoulder : 0.92 ~ 0.94
      ii. left_wrist ↔ right_wrist : 0.83 ~ 0.85
      iii. **shoulder ↔ wrist relationship : 0.64 ~ 0.78**
      iv. Detecting actions such as sudden hand waving or arm raising
   d. **Lower Body**
      i. left_knee ↔ right_knee,
      left_ankle ↔ right_ankle : 0.77 ~ 0.92
      ii. **ankle ↔ knee relationship : 0.58 ~ 0.77**
      iii. Situations where a pedestrian suddenly dashes into the road or shows a rapid change in movement speed
   e. **Mixed Body**
      i. Upper body (shoulders, wrists) ↔
      Lower body (knees, ankles) : 0.1 ~ 0.3



Data Analysis 3.2

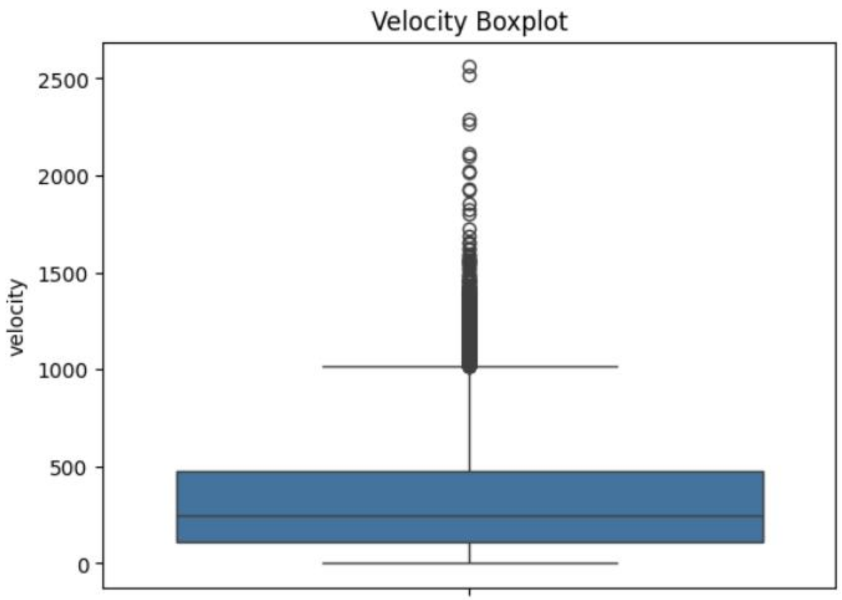
4. **Keypoint Selection and Velocity Pattern Analysis**
    a. Sudden changes in keypoint velocity over time → Labeled as unexpected behavior.
    b. (x, y) coordinates → Euclidean distance-based speed calculation → Action counting
    c. **Upper Body**
        i. Normal : 117,681 (85%)
        ii. High Speed : 22,127 (15%)
        iii. Irregular : 576 (0.4%)
    d. **Lower Body**
        i. Normal : 40,874 (59%)
        ii. **High Speed : 28,558 (40%)**
        iii. Irregular : 760 (1.2%)
        iv. High proportion of high-speed movement in lower body → Key indicator of locomotion-related behavior
    e. **Mixed Body**
        i. Normal : 99,103 (69%)
        ii. **High Speed : 40,285 (29%)**
        iii. **Irregular : 996 (2.4%)**



5. **Labeling for Model Training**
   a. Median : 250 ~ 300
   b. Upper Whisker : 1000, beyond values → Outliers
   c. Outliers (velocity > 1000) → Irregular
   d. Labeling Criteria
      i. **Normal (0) : 0–500 *pixels/frame***
      ii. **High Speed (1) : 500–1000 *pixels/frame***
      iii. **Irregular (2) : Above 1000 *pixels/frame***
   e. Add velocity, acceleration, motion_category(0~2), group(lower/upper/mixed) column.

   ———————————————————————————

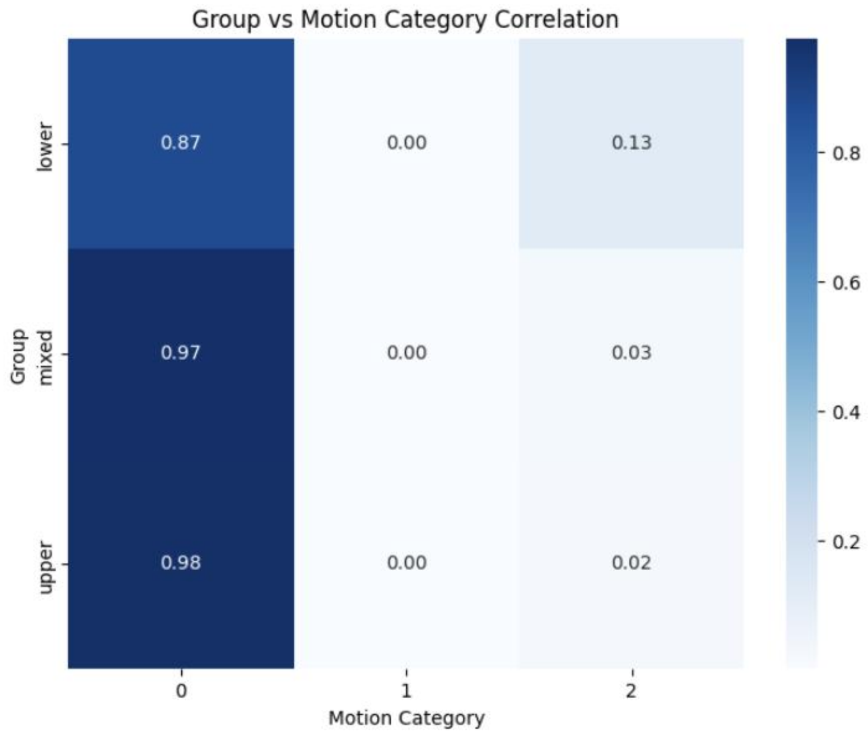
   f. *[Reference] Metadata details (`Clip_info`)*
      i. Annotation: Keypoint positions for each movement at 60 FPS
      ii. Resolution: Captured in 4K (3840×2160 pixels)



6. **Group vs Motion Category CrossTab**
   a. output

motion_category	0	1	2
group			
lower	61031	212	8949
mixed	68071	149	1972
upper	136976	290	3118

   b. **Normal (0)**
      i. Upper : 98 %
      ii. Lower : 87 %
      iii. Mixed : 97%
   c. **High Speed (1)**
      i. 0% high-speed movement detected in all groups
   d. **Irregular (2)**
      i. Upper : 2%
      ii. Lower : 3%
      iii. Mixed : 13%



03. Model Development

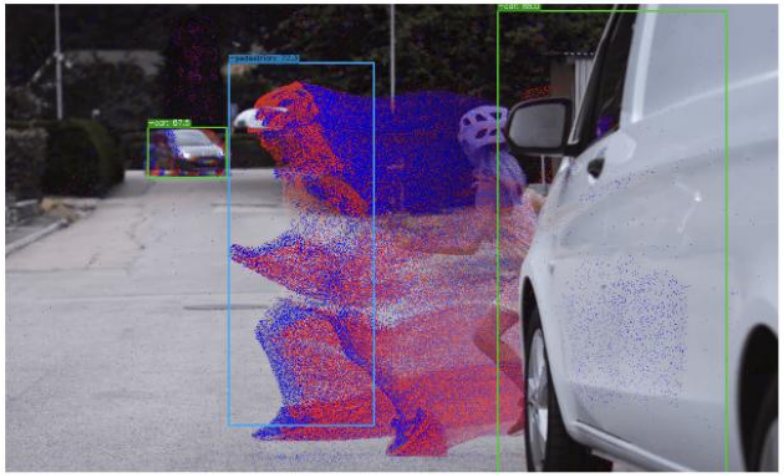
- Train Tutorial

Model Development

03

🤖 ***Train Tutorial***

1. YOLO Data Preparation
    a. Extracted Class IDs and Bounding Boxes, Saved as `.txt` files.
2. Mask R-CNN Data Preparation
    a. Extracted a single COCO-format JSON file for model training (Bounding Box, Segmentation Masks, Class ID).
3. Special Features
    a. Frames with significant speed changes : Tagged as ‘acceleration’.
    b. ‘Irregular’ tag assigned to frames showing abnormal behavior patterns.
    c. [Reference] See Section #02: Data Analysis.
4. Data Augmentation
    a. flipping, rotation, cropping, brightness changing etc.



참고) [*Hybrid Camera Targets Self-Driving Car Safety*]

04. Conclusion

- Trouble Shooting (Limitation)
- Future Plan

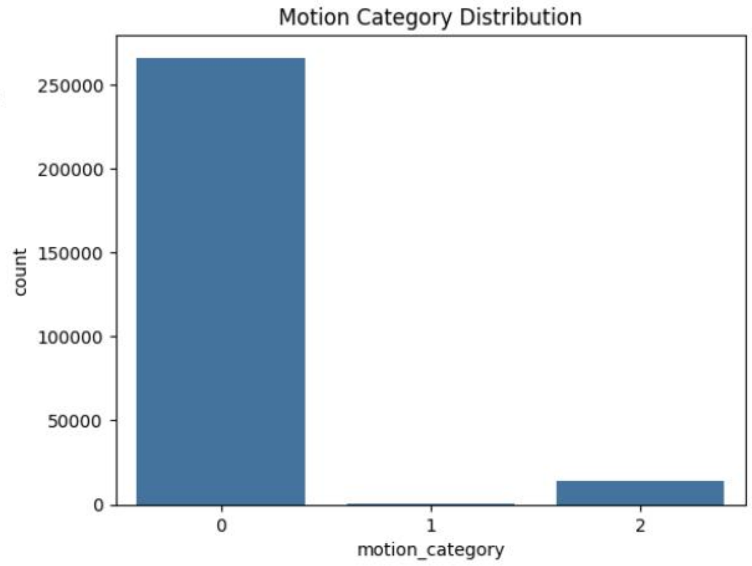
Trouble Shooting

🚧 ***[limitation]***

The challenge in detecting unstructured data lies in the inherent limitation of how closely mask dance movements resemble real-world pedestrian behavior.

1. **Generalizability of the Data**
    a. Although mask dance data was used under the assumption that it provides unstructured movement patterns, it cannot fully represent abnormal pedestrian behavior.
    b. To address this, incorporating real-world data such as jaywalking CCTV footage is necessary for further model validation.

2. **Ambiguity in defining speed and acceleration thresholds**
    a. Faced challenges in setting thresholds for labeling.
    b. Motion category distribution was highly imbalanced.
    c. Used IQR to define a normal range :
    `{normal_min}` ~ `{normal_max}`
    → Need to address data imbalance for future model training.



Future Plan

🏁 ***[Future] Trained a YOLO-based pedestrian detection model using image data***

1. **YOLO-based Training** : Developed a pedestrian detection model using image data.
2. **Focus on Irregular Behavior :** Improved detection by including lower-body and mixed group data.
3. **Performance Evaluation:** Measured detection performance using Accuracy, Precision, Recall, and F1-Score.
    a. Compared prediction results across upper-body, lower-body, and mixed joint data.