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A SURVEY OF DATASETS, APPLICATIONS, AND MODELS FOR IMU SENSOR SIGNALS

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ABSTRACT

Inertial Measurement Units (IMUs) are small, low-cost sensors that can measure accelerations and angular velocities, making them valuable tools for a variety of applications, including robotics, virtual reality, and healthcare. With the advent of deep learning, there has been a surge of interest in using IMU data to train DNN models for various applications. In this paper, we survey the state-of-the-art ML models including deep neural network models and applications for IMU sensors. We first provide an overview of IMU sensors and the types of data they generate. We then review the most popular models for IMU data, including convolutional neural networks, recurrent neural networks, and attention-based models. We also discuss the challenges associated with training deep neural networks on IMU data, such as data scarcity, noise, and sensor drift. Finally, we present a comprehensive review of the most prominent applications of deep neural networks for IMU data, including human activity recognition, gesture recognition, gait analysis, and fall detection. Overall, this survey provides a comprehensive overview of the state-of-the-art deep neural network models and applications for IMU sensors and highlights the challenges and opportunities in this rapidly evolving field.

1. INTRODUCTION

Inertial Measurement Units (IMUs) are small, low-cost sensors that have become ubiquitous in a variety of applications, from robotics to healthcare. These sensors can measure accelerations and angular velocities and provide valuable information for many tasks such as activity recognition, gesture recognition, and gait analysis. In recent years, there has been a surge of interest in using deep learning techniques to analyze IMU data, enabling the development of accurate and robust models for these applications.

Deep neural networks (DNNs) have emerged as a popular tool for analyzing IMU data due to their ability to learn complex features and relationships from raw sensor data. However, IMU research has been challenging due to the absence of standardized benchmark datasets and inconsistent data formats across different datasets. Also applying deep learning techniques to IMU data poses significant challenges such as scarcity of in-domain data, as well as sensor bias, drift and noise that can affect the accuracy of the models.

In this paper, we provide a comprehensive survey of the current state-of-the-art deep neural network models and applications for IMU sensors, providing a valuable resource for researchers and practitioners interested in applying IMU data for various applications. Additionally, we provide an overview of the most popularly used IMU sensors and the prominent applications of deep neural networks for IMU data, including human activity recognition, gesture recognition, gait analysis, and fall detection. We also discuss the specific challenges and opportunities for using deep neural networks, as well as the state-of-the-art results achieved by existing models.

The rest of the paper is organized as follows: Section 2 provides an overview of the applications of IMU sensors in both industry and academia. Section 3 summarizes the publicly available datasets in these domains. We then review the most common pre-processing methods and state-of-the-art models for each application and dataset in Section 4.

2. IMU APPLICATIONS

2.1. IMU Devices

The output of an IMU sensor is typically a time-series of measurements, which can be processed to extract useful information about the object's motion and orientation. Depending on the application, different types of IMU sensors and devices may be used, each with varying degrees of sampling rate, location of IMU mount (like head mount or armbands), accuracy, precision, and cost. Table 2 summarizes various publicly available IMU sensors and devices. For most of the applications, the tri-axial accelerometer and gyroscope readings are sufficient. The applications requiring localization or positioning estimates often use magnetometer

2.2. Domains of IMU Applications

IMUs have found applications in a wide range of domains, including healthcare, robotics, sports, and many others. In this section, we survey the recent literature in detail for each of the applications. Table 3 summarizes the domains and use cases of IMU sensor signals.

IMU sensors are very widely used in **healthcare and clinical diagnosis**. For example, IMUs have been used to monitor patients' activity levels, detect falls, and analyze gait patterns.

ML Problem	Location	Freq	Modalities	Ref
Fall Detection	Multiple positions	NA	IMU only	[1]
Fall Detection	Abdomen	100Hz	IMU only	[2]
Fall Detection	Abdomen	51Hz	IMU + ECG	[3]
Freeze of gait detection	Ankle	128Hz	IMU + Camera	[4]
Gait Analysis	Ankle + reflexive markers	100Hz	IMU + Camera	[5]
3D Pose estimation	Multiple positions	148Hz	IMU + Camera	[6]
Activity Recognition	Multiple positions	NA	IMU + Camera	[7]
Activity Recognition	Head	50Hz	IMU only	[8]
Activity Recognition	Multiple positions	100Hz	IMU only	[9]
Activity Recognition	Abdomen	51Hz	ECG only	[3]
Activity recognition	Multiple positions	60Hz/100Hz	IMU + barometer data	[10]
Continuous Activity Recognition	Right wrist	50Hz	IMU only	[11]
Egocentric Action detection	Head mounted	NA	IMU + Camera + flow frames	[12]
Gesture Recognition	Armband	50Hz	IMU + EMG	[13]
Gesture(finger) recognition	Finger	synthetic data	Video $\hookrightarrow IMU$	[14]
Head tremor detection	Head	100Hz	IMU + Camera	[15]
Velocity Monitoring	Benchpress	100Hz	IMU + Camera	[16]
Stereo-VIO	Car	400Hz	IMU + Camera	[17]
Speed Estimation	Head	100Hz	IMU only	[18]

Table 1. High level overview of imu datasets

IMU Sensor	Location	Ref
Thalmic Lab's MYO	Armband	[13]
Recon Jet	Eye wear	[18]
Sensixa e-AR	Ear	[18]
InvenSense (MPU-9150)	Abdomen	[2]
emteqPRO VR device	head	[8]
Noraxon myoMotion	multiple locations(8)	[9]
Apple Smartwatch	wrist	[11]
MbientLabs	finger	[14]
SHIMMER3	waist	[3]
InvenSense MPU-9250	ankle	[5]
MTw Awinda sensor	head	[15]
Xsens MTw	object/body	[16], [10]
C100-F9K GNSS-IMU	car	[17]

Table 2. Commercial IMU sensors

Domain	ML Task	Ref
HCI/Mixed Reality	Gesture recognition	[13], [14]
Clinical Diagnosis	Gait analysis	[4], [5]
Clinical Diagnosis	3d pose estimation	[6]
Clinical Diagnosis	Head tremor detection	[15]
Elderly Care	Fall Detection	[2], [3], [1]
Elderly Care	Activity Recognition	[3], [9], [11]
Sports	Activity recognition	[8]
Sports	Speed estimation	[18], [10], [11]
Sports	Tracking Positions & Speed	[16], [7]
Robotics	Odometry	[17]

Table 3. IMU application domains and their usage

IMUs sensors are often attached to a patient's body to measure the acceleration and angular velocity of different body parts during walking, which can be used to detect abnormalities in gait patterns that may indicate underlying health conditions. For example, Santosh et al. [5] uses 42 reflective markers on a subject with IMU data and video data for gait analysis. IMU data in combination with video and psychiatric scales has also been used for freeze of gait detection in individuals with Parkinson's disease [4]. Moniruzzaman et al. [6] uses data from 8 IMUs and 2 cameras for 3D pose estimation for helping amputees obtain an optimal walking condition with predictive control. [19] uses IMU sensor placed on ankle for predicting the next foot placement of humans during walking for improving walking aid exoskeletons for patients.

Fall detection using IMU sensors is also very prominent in clinical research. Kim et al. [9] uses 8 IMU sensor data attached to different parts of the body for 14 static and dynamic motions mentioned in Berg Balance Scale for assessing the probability of fall in an elderly patient. Chen et al. Soonjae Ahn et al. [2] uses a combination of vector sum of acceleration axis, vector sum of pitch and roll, triangle feature and verticle angle computation to predict the likelihood of a fall. Nadeem et al [3] used IMU and ECG signals for analyzing fall detection, activity prediction and basic heat anomaly detection

Other motion based applications in clinical research include prediction of amplitude and frequency of head movements in patients with head tremor using video and IMU analysis. [15].

In **robotics and human computer interaction** domain, IMUs have been used for gesture detection and hand tracking purposes. Using video for gesture detection is a mature domain but it is power hungry. Liu et al. [14] uses IMU sensor on finger to track gestures for lighter weight use cases by harvesting training data from public videos for performing inferences on IMU (extracting motion data from videos and transforming them into acceleration and orientation information measured by IMU sensors). Similarly, Jiang et al [13] uses both IMU and EMG signals for gesture recognition for multiple HCI use cases. Continuous activity recognition on smart watch users is yet another example of HCI use case for ambient contextual understanding of a user [11]

In **sports and fitness**, IMUs have been used to track movements of athletes, estimate velocity and analyze performance metrics. For example, [18] uses head worn IMU sensor for estimating walking speeds for health monitoring. IMU signal in combination with GPS signals (lower sampling rate) can also provide reliable distance estimation. In strength training, [16] uses IMU sensors on barbell to monitor velocity of bench press for improved performance metrics. They show that there is a high correlation between IMU based predictions and video based velocity monitoring

IMUs are also used widely in smartphones for assessing orientation of the phone, device placement (fixed hand, swinging, in pocket or backpack) and user motion (still, walking, running) [10]. Given the ubiquity of smartphones and easily accessible IMU data on them, Mourcou et al. even explored the possibility of using smartphones for clinical motion research[20].

3. IMU DATASETS

In this section, we summarize the publicly available datasets that include the IMU signals (Table 1).

Chen et al. [17] collected a novel dataset of stereo inertial data using an SUV equipped with a GNSS-IMU device with kinematic correction signals, to aid in various applications such as Visual-Inertial Odometry (VIO), Simultaneous Localization and Mapping (SLAM), and object detection. This dataset is multimodal, comprising synchronized IMU data (at 400Hz), stereo images, and 6DOF data. To ensure accurate annotations, intrinsic and extrinsic calibration was carried out for the stereo camera, built-in IMU, and GNSS-IMU navigation device. The timestamp of the sensor messages is synchronized and augmented to facilitate evaluation.

Epic-Kitchen [12] consists of 100 hours of multimodal data, including RGB and Flow frames, as well as gyro and accelerometer data. It comprises 90,000 action segments and 20,000 unique narrations. Additionally, the dataset provides annotations for masks, hands, and objects. This dataset has been used for various challenges, including action recognition & detection, action anticipation, multi-instance retrieval, and unsupervised domain adaptation for action recognition.

Santos et al. [5] collected a dataset of gait analysis data using an InvenSense MPU-9250 IMU device (6 axis) sampled at 100Hz. The dataset includes data from 25 participants, with extensive details provided for each subject. The gait analysis was carried out using 42 reflective markers on each subject, with cameras sampling at 100Hz. The authors used polynomial interpolation to fill in gaps and relational interpolation based on the position of the surrounding markers for data preprocessing. This dataset holds great potential for advancing research in IMU-based gait analysis, and the techniques used for data preprocessing could be useful for future research.

Pre-processing method	ref
Data Segmentation + Normalization	[13], [8], [9], [11]
LPF Butterworth filter	[18], [2],[8], [14], [4], [16]
Time domain & FFT features	[18], [2], [6], [16]

Table 4. Popular pre-processing methods for IMU

In medical domain, [4] collected a dataset with video, IMU (kinematic data), annotated with cognitive or psychiatric scales in patients, which can be used for estimating FoG in Parkinson's disease patients. The IMU signals were sampled at 128Hz and filtered using a fourth-order zero-phase Butterworth filter with a 60-Hz cutoff frequency.

Kasebzadeh et al. [10] created a dataset for motion and device mode classification, comprising IMU and barometer data collected from eight participants using a smartphone and 17 other locations on the body, providing rich data for multiple applications. The data was sampled at 60Hz and 100Hz using two different devices. This dataset has the potential to contribute to research in various fields, including activity recognition and gait analysis, and could also be useful for developing and testing wearable technology.

Casilari et al. [1] released the UMAFall dataset, a repository of movement data for day-to-day activities and falls. This dataset is specifically designed to study the effectiveness of fall detection algorithms based on the placement of sensors. The dataset includes accelerometer data collected from four IMU sensors located on the chest, waist, wrist, and ankle. Accelerometer data is commonly used for fall detection, as falls trigger unexpected peaks in the accelerometer data, and in a free fall, the accelerometer data rapidly decays to 0.

Another similar dataset includes [3], which presents a multimodal dataset for activity recognition, fall detection and basic heart anomaly detection system, comprising ECG (4 axis) and IMU (SHIMMER device; 51 Hz) sensor data.

4. IMU SIGNAL PROCESSING AND MODELING

In this section, we provide a survey of the signal processing and modeling methods for IMU data.

Table 4 summarizes the popular pre-processing methods for IMU.

There is no standard format for storing IMU data. For example, the three axis of gyroscope data can be in radian/s vs degree/s. Accelerometer data in some sensors account for gravitational force while some do not. Thus using IMU data from multiple sources need to be factorized to be brought to the same units before being fed into the model.

Moreoever, IMU sensor data suffers from several issues including transmission latency (i.e the time lag between

ML Model	Ref
ConvNet	[13], [14], [7]
Gaussian Process Regression	[18]
Feature extraction + thresholding	[2]
Feature Extraction + KNN	[8]
1D CNN heads + GRU ensemble	[9]
BiLSTM	[11]
Attention Oriented RNN	[6]

Table 5. Various IMU machine learning models

when the timestamp was collected vs recorded), bias, drift and noise. [21]. Bias is addressed by accounting for a bias offset in the calibration process (Orientation filters like complementary filter, Kalman filter and Madgwick [13] are used for addressing sensor bias) while the drift is modelled as a stochastic process to reduce the estimated error.

Noise is often removed by passing the IMU signals through the low pass butterworth filters. Depending on the use case, the tri-axial data uses different low pass filters at different cutoff frequencies(ex: 5s, 8s, 10s, 60s [18], [2], [14], [4]). Once bias, drift and noise have been accounted for normalization and zero-padding is also carried out as pre-pricessing steps. [9]. Sometimes, for imbalanced datasets, data oversampling has also been used for data augumentation.[9].

After the above pre-processing steps, the time series IMU data is segmented into windows of different seconds. For example, in [18], 5s of IMU data is used to define one sample. In case of mulitmodal data, the same length of segmentated windows are aligned for all modalities. For example, in gesture recognition using EMG and IMU data [13], 1s of pre-processed modality aligned data is fed into the two-stream CNN model.

Once the data is pre-processed and segmented, usually hand crafted features are extracted from IMU data for statistical analysis or to be fed into traditional ML models like SVM and KNN. The next section surveys different kinds of ML models. Table 5. summarizes the popular models IMU.

[2] uses a heuristic model based on the four features (triangle feature, verticle angle, sum vector of acceleration and sum vector of pitch and roll) for their pre-impact fall detection algorithm. [19] uses Bayesian inference-based foot placement prediction approach. [15] quantified the amplitude and frequency of head movements in head tremor patients using IMU features time domain features like peak-to-peak and frequency domain features like mean frequency of the power spectrum.

Zihajehzadeh et al. [18] uses Gaussian process regression model for measuring walking speeds after extracting time-domain features like mean absolute value, median, mod, standard deviation, signal magnitude area, energy and number of mean crossing and frequency-domain features (512-point fast Fourier transform (FFT) is used within each 5-s window and the magnitude of FFT coefficients are used as frequency-domain features) along with anthropomorphic features like height and weight of the subjects.

Moniruzzaman et al. [6] does 3D pose estimation which extracts 3 channel acceleration, 3 channel angular velocity, and orientation features (3×3 rotation matrix) along with histogram of optical flow features from video data. This is then fed into Attention-Oriented Recurrent Neural Net- work (AttRNet) which comprises of sensor wise encoder, recurrent encoders, reconstruction module and finally an attention-oriented recurrent decoder which outputs a series of future poses from the encoded features of different time steps using the dynamic temporal attention module.

Kim et al. [9] describes a 2 1-D CNN heads with GRU head ensemble model for human activity recognition task. Jiang et al. [13] have experimented with 2 stream CNN and RNN model architectures for gesture recognition where CNN model outperforms all other methods. For continuous activity recognition model, a Bi-directional LSTM correctly predicted the stream of activities using imu data of smartwatches.[11]

5. CONCLUSIONS

In this survey, we provided a comprehensive overview of the state-of-the-art deep neural network models and applications for IMU sensors.

IMUs have a wide range of applications in various domains, and their versatility and low cost make them an attractive choice for many tasks that require motion sensing and orientation tracking. The use of deep neural networks to process IMU data has enabled the development of more accurate and robust models for these applications, opening up new possibilities for IMU-based sensing and control in the future.

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