ヘルスケア・高齢者向け

登壇者名	山口 栄太
所属等	WonderWonder
連絡先	contact@wonder-wonder.xyz

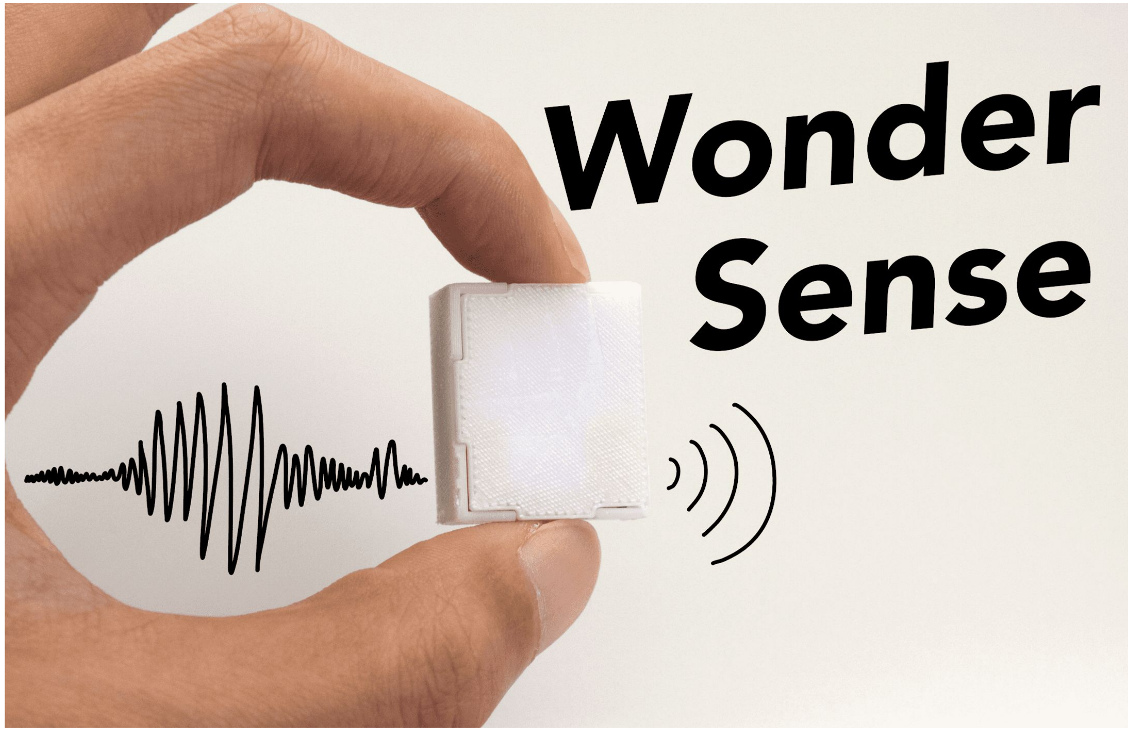
法人設立予定時期（西暦）	2021年（設立に向けて準備中）
事業活動拠点都道府県	福島県
個人SNS等	https://wonder-wonder.xyz/daily
事業プラン名	ウェアラブルデバイスとAIを利用した 安心安全な高齢者の見守りシステム（Daily)
事業プラン概要	我々が独自に開発しているウェアラブルデバイスとデータ処理・解析技術を利用した高齢者の見守りシステムを、見守りサービス事業者やサービス付き高齢者住宅を提供している事業者の方々へ提供します。 現在主流な見守りシステムは、設置型やボタンを押すようなものですが、転倒のような突発的な問題に対処するためには、検出範囲や動作に限界があります。我々のシステムでは、自発的な行動をしなくても、AIを使い転倒などの突発的な動作を自動検出します。また、生活リズムを解析することで異常を検出し、高齢者の家族などにメールやアプリを通して通知することが可能なシステムを提供します。 今まで見守りサービスにかかっていた開発・導入コストを圧倒的に抑えることができます。また大学研究室と連携し日々研究を重ね性能の向上を図ります。そして、アプリを通して高齢者の状況を把握できる家族も安心できるサービスを提供します。
福島/本プログラムにかける想い	高齢化が進む日本において、高齢者のサポートシステムの存在はかなり重要なものになってくると考えています。約10年前の震災を経て新たな産業として、福島での実証実験からこのシステム、もしくは利用したサービスを全国へ広げて行きたいと考えています。
イベントにご参加いただく方への一言	イベントにご参加頂きましてありがとうございます。我々の持つデータ処理やウェアラブルセンサーの開発技術は、今後の高齢者サポートに対して重要なものになってくると考えています。ご興味を持たれた方、実証実験にご協力していただける方はぜひご連絡頂ければ幸いです。また上記のWebサイトを御覧頂ければ幸いです。

発表資料

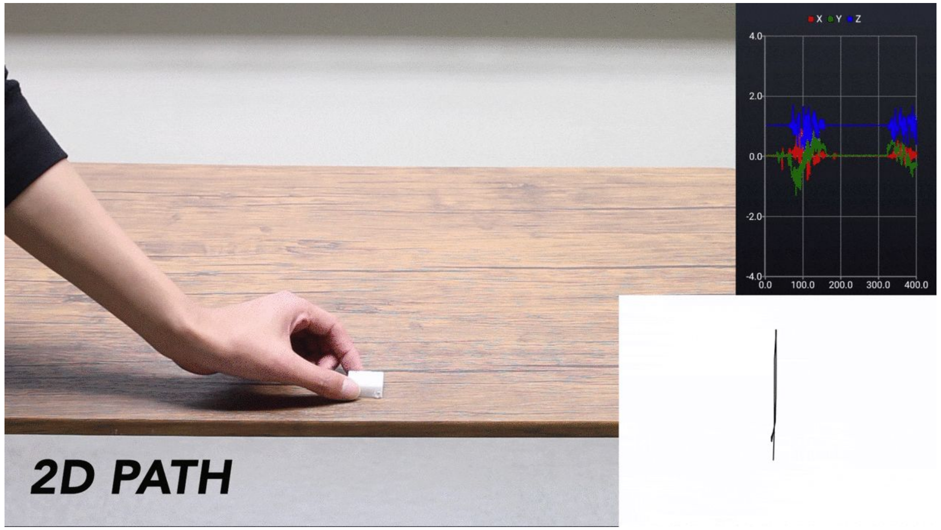
Daily

「見守り」をもっと手軽にスマートに。

動きの
デジタル化

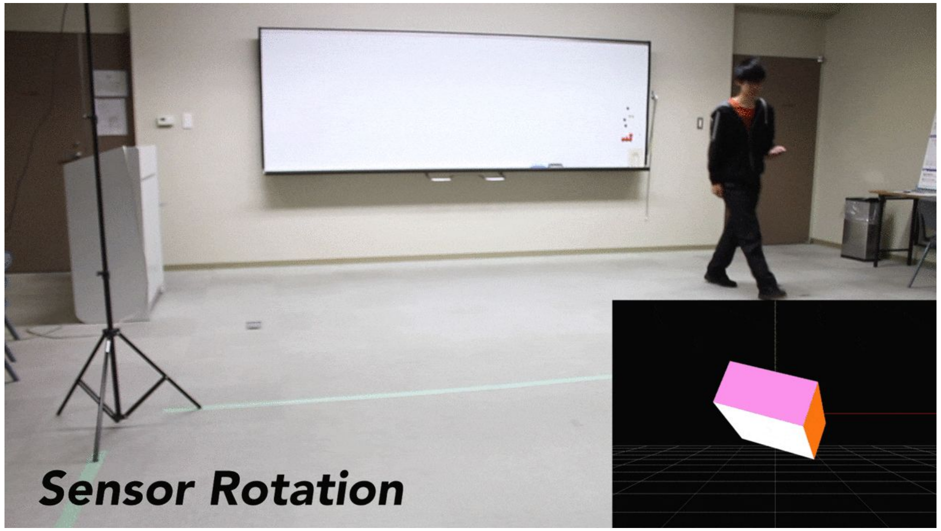


WonderWonder



2D描画

歩行のトラッキング



チームメンバー

今までに複数のシステム開発を経験。学生時代は、WonderSenseを利用して行動認識を研究。WonderSenseの有用性に強く惹かれ、WonderWonderを創立。現在、ベンチャー企業でエンジニアとしても働く。

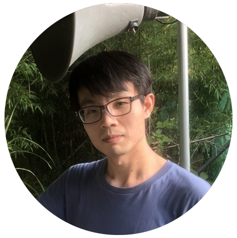
代表　山口 栄太

動作追跡システムについて、15年の研究開発の経験。WonderEngineプラットフォームを提案。指輪、歯ブラシ、手袋などの動作追跡システムを開発。動作追跡について、特許3個、論文多数

代表　荊 雷

学生時代、アプリ開発やモーションセンサーのデータ処理、機械学習を使った行動認識を研究。
現在、ソフトウェア会社でシステムエンジニアとして働く。

沼波 佑樹



中国江蘇省出身
カルマンフィルタを用いた姿勢推定を専攻し、組み込みシステム開発とデータ分析について深い知識を持つ。
WonderWonderではハードウェア開発をすべて担う。

戴 澤陽

大学内で使用されているソフトウェア開発などを行う。
シリコンバレーの企業でインターンシップに参加し、機械学習などを学ぶ。セキュリティから低レイヤーまで幅広い知識を持つ。

並木 優祐

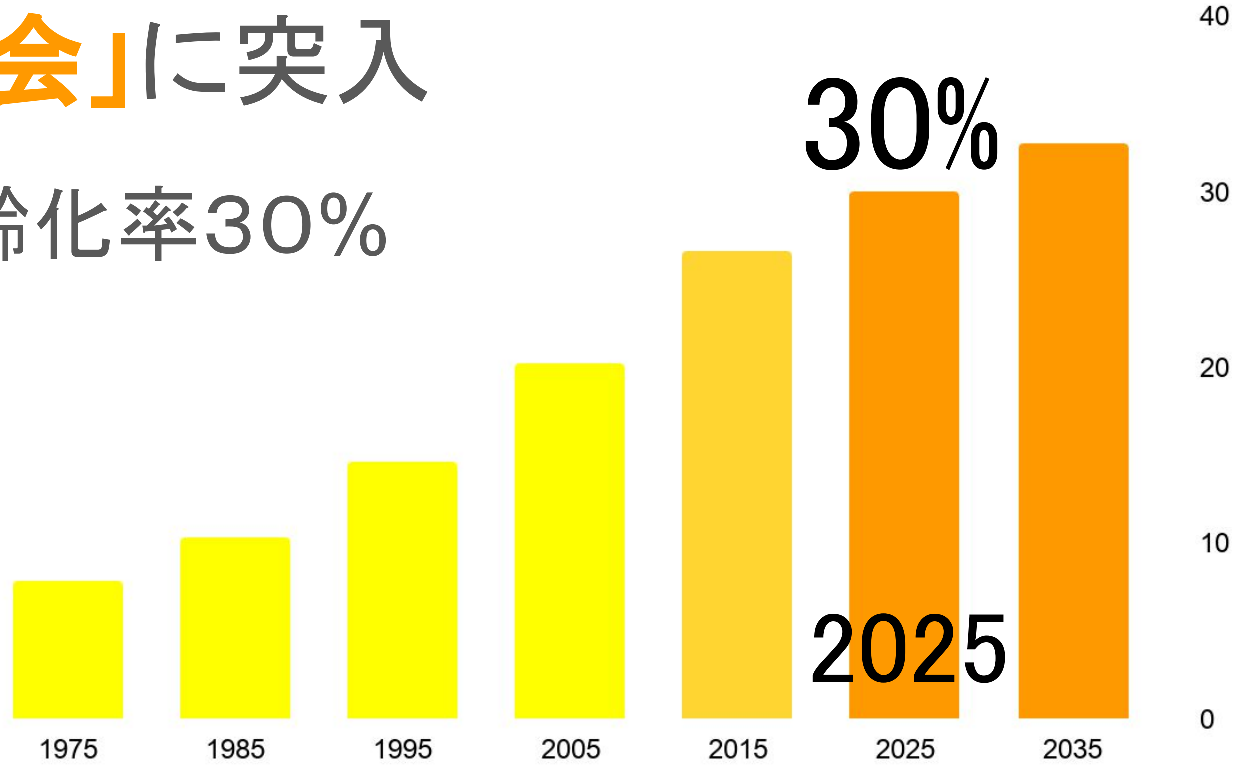
触覚による遠隔コントロール支援の研究や、触錯を応用したVRコンテンツの制作等を行っている。
Wonder Senseの VR /AR コントロール利用に関心を寄せている。

星 裕也

日本の現状

「超高齢化社会」に突入

2025年には高齢化率30%



出典：令和2年版高齢社会白書（内閣府）

日本の現状

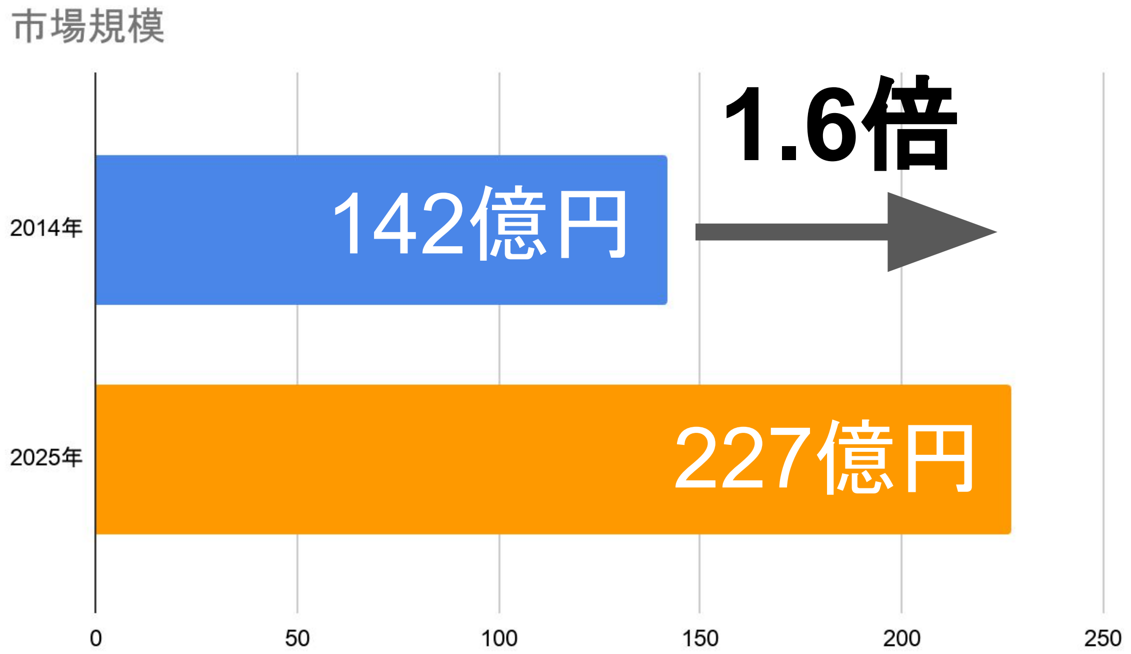
「見守りサービス」の需要が増加

2018年には
世帯の約半数に65歳以上の高齢者

出典：令和2年版高齢社会白書（内閣府）

市場規模

高齢者見守り･緊急通報サービスの国内市場



出典:SEED PLANNING 高齢者見守り･緊急通報サービスの市場動向

見守りサービスの現状

製品例

設置型のセンサー

ボタン式

カメラ式

Panasonic

ホームネットワークシステム
人感センサー
KX-HJS200-W

見守りサービスの現状

設置型のセンサー や **カメラ式** だと

検出できる範囲に限界がある

見守りサービスの現状

ボタン式の場合

倒れる(れた)際に、

自らボタンを押すことは難しい

見守りサービスの現状

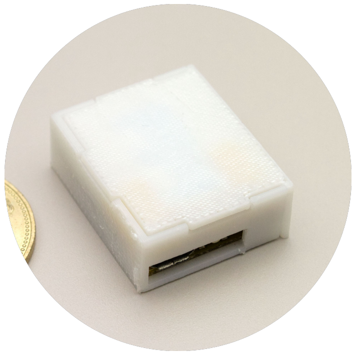
転倒の自動検出ができるデバイス

- **多額の開発・導入コスト**
- **誤検知が多い**

製品例

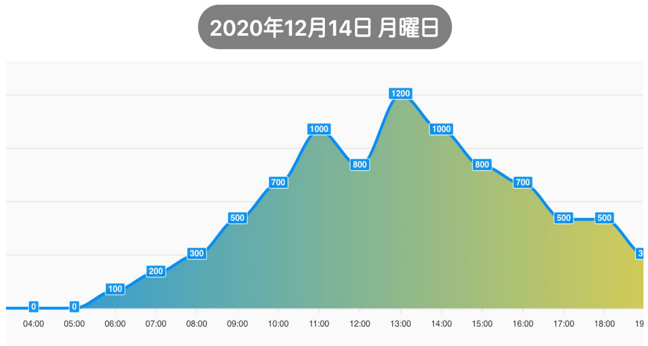
事業内容

高精度で安価な見守りサポートシステム
Daily の提供



ウェアラブル
センサー

データ処理



データの可視化

システム

運動量　　転倒

生活リズムの変化

異変を自動検知！

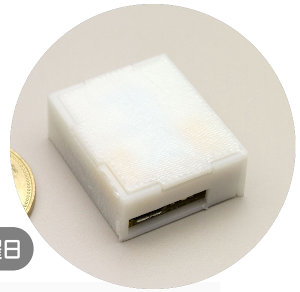
家族や見守り事業者に通知

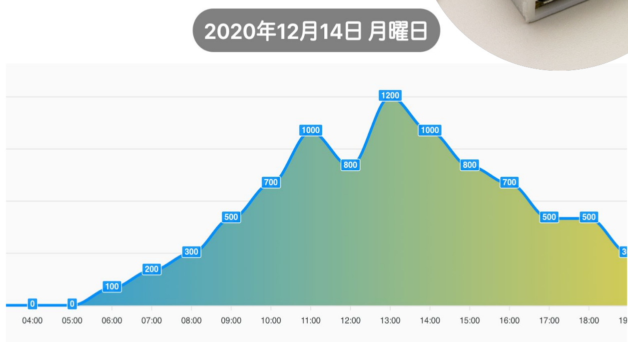
価値

開発・導入・運用コストを**圧倒的に削減**

- デバイスは**レンタル**
- サービスは**クラウド**
- **利用人数**に応じて課金

1000円 × 人数



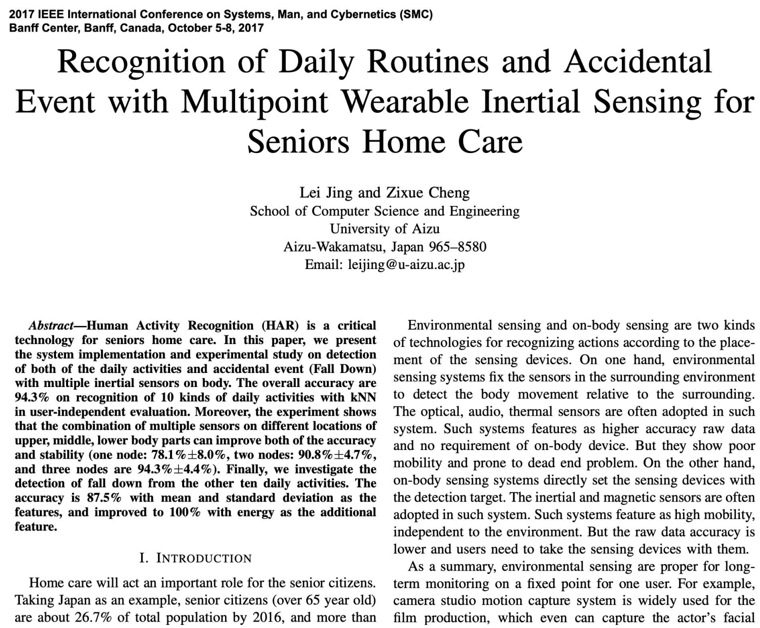


価値

誤検知の少ないシステム

日々性能の向上

- 大学研究室と連携
- 最新の研究結果を反映


2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)
Banff Center, Banff, Canada, October 5-8, 2017

Recognition of Daily Routines and Accidental Event with Multipoint Wearable Inertial Sensing for Seniors Home Care

Lei Jing and Zixue Cheng
School of Computer Science and Engineering
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Aizu-Wakamatsu, Japan 965–8580
Email: leijing@u-aizu.ac.jp

***Abstract*—Human Activity Recognition (HAR) is a critical technology for seniors home care. In this paper, we present the system implementation and experimental study on detection of both of the daily activities and accidental event (Fall Down) with multiple inertial sensors on body. The overall accuracy are 94.3% on recognition of 10 kinds of daily activities with kNN in user-independent evaluation. Moreover, the experiment shows that the combination of multiple sensors on different locations of upper, middle, lower body parts can improve both of the accuracy and stability (one node: 78.1%±8.0%, two nodes: 90.8%±4.7%, and three nodes are 94.3%±4.4%). Finally, we investigate the detection of fall down from the other ten daily activities. The accuracy is 87.5% with mean and standard deviation as the features, and improved to 100% with energy as the additional feature.**

I. INTRODUCTION

Home care will act an important role for the senior citizens. Taking Japan as an example, senior citizens (over 65 year old) are about 26.7% of total population by 2016, and more than

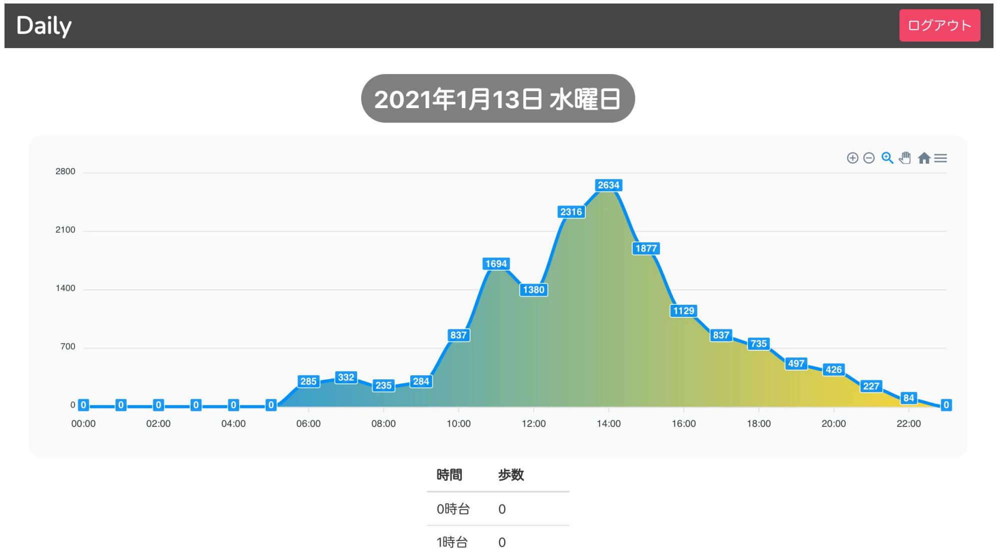
Environmental sensing and on-body sensing are two kinds of technologies for recognizing actions according to the placement of the sensing devices. On one hand, environmental sensing systems fix the sensors in the surrounding environment to detect the body movement relative to the surrounding. The optical, audio, thermal sensors are often adopted in such system. Such systems features as higher accuracy raw data and no requirement of on-body device. But they show poor mobility and prone to dead end problem. On the other hand, on-body sensing systems directly set the sensing devices with the detection target. The inertial and magnetic sensors are often adopted in such system. Such systems feature as high mobility, independent to the environment. But the raw data accuracy is lower and users need to take the sensing devices with them.

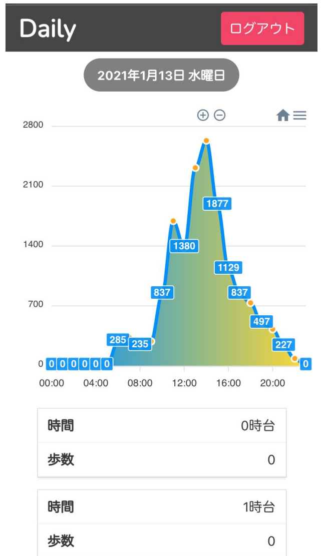
As a summary, environmental sensing are proper for long-term monitoring on a fixed point for one user. For example, camera studio motion capture system is widely used for the film production, which even can capture the actor's facial

価値

見守りサービスに対する

顧客満足度・安心感の向上





今後の展開

ヒヤリング継続
プロトタイプ開発

2021/01 ~

実証実験

2021/04 ~

サービス連携

2022 ~

最後に

現在探しています！

- 実証実験に協力していただける
  見守りサービスを活用したい方々

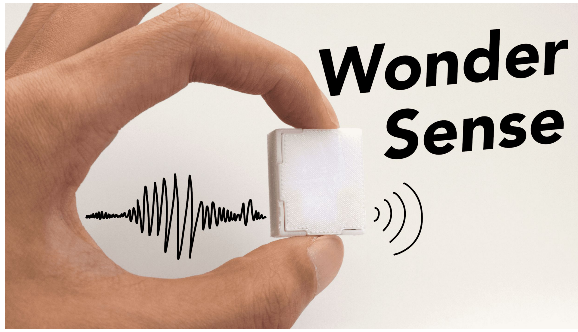
- サービス開発に投資していただける方

WonderSenseについて

WonderSenseの紹介

WonderWonder

概要



→ 機能説明

→ 仕様

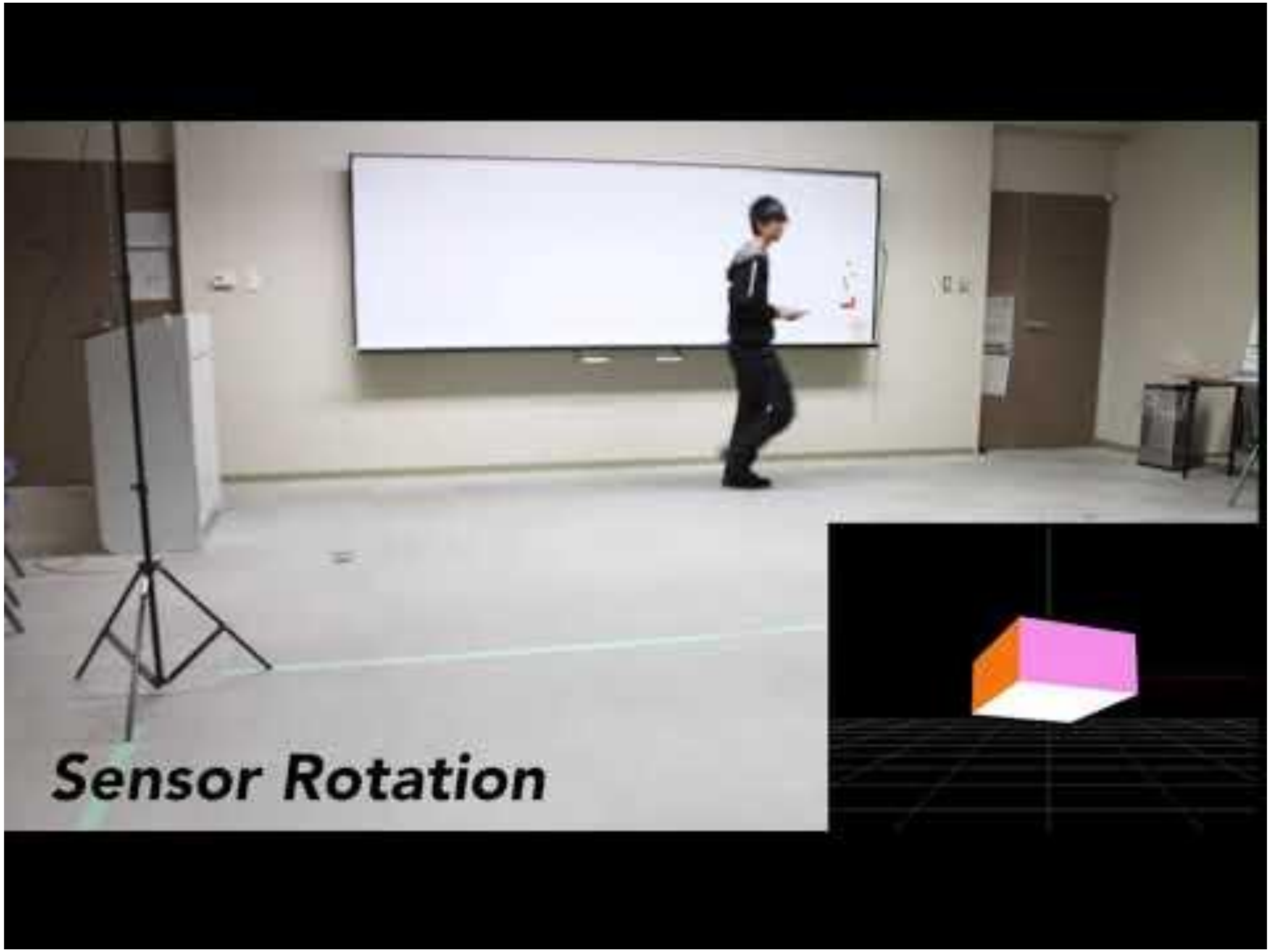
→ ユースケース

機能説明

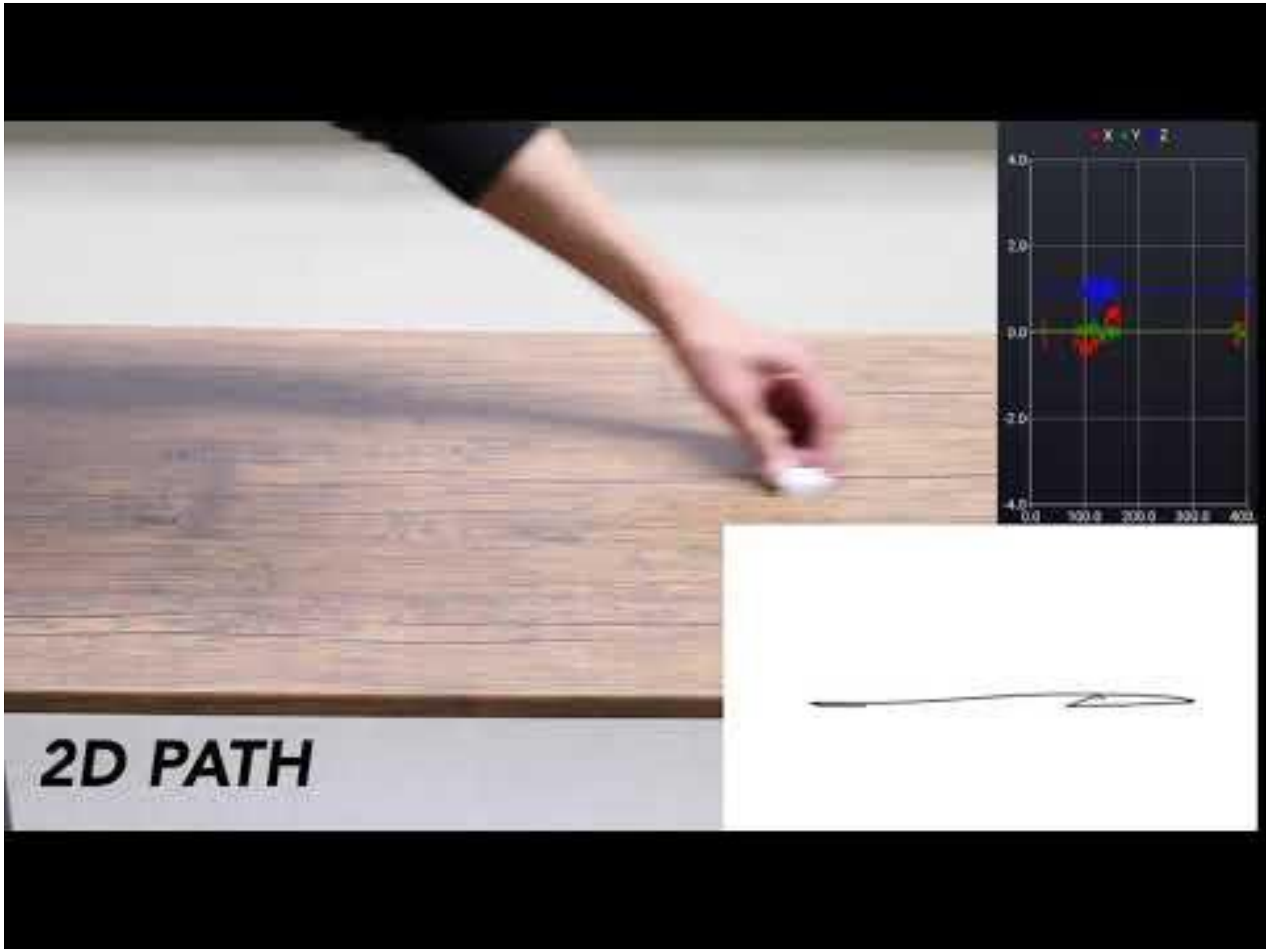
- ➔ センサーを用いてモーションのサンプリング
- ➔ 最大300hzのサンプリングデータをリアルタイムに転送
- ➔ サンプリングされたデータを用いて
  - ◆ 動作の検出
  - ◆ センサーの大まかな回転検出
  - ◆ ごく短期間の移動方向検出

https://www.youtube.com/watch?v=Q-ip3I4Gj_s

https://www.youtube.com/watch?v=LsMSliBsfdE



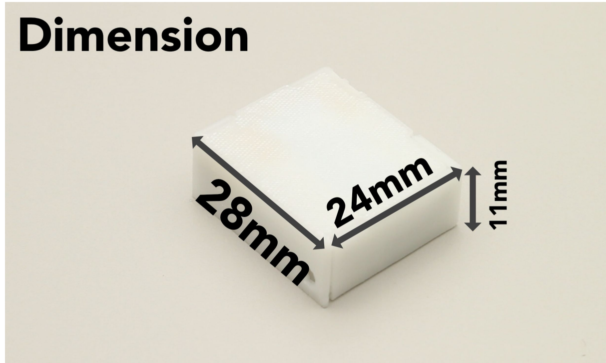
https://www.youtube.com/watch?v=SvbPdXOt3SE

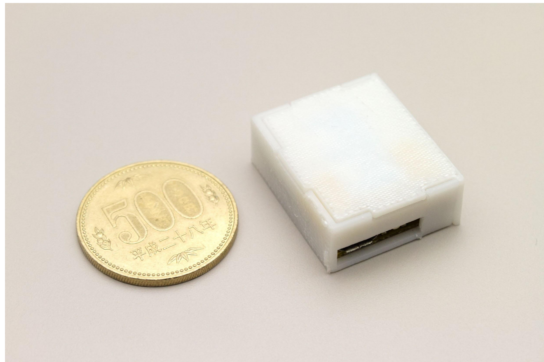


https://www.youtube.com/watch?v=Mwt9nVfhXI8

仕様

- ➔ 28mm * 24mm * 11mmの腕時計サイズ
- ➔ 7.7gの軽量
- ➔ BLE4.2を用いたワイヤレス通信
- ➔ 対応プラットフォーム
    - ◆ Android / iOS





仕様

- ➔ BLE4.2
- ➔ 対応プラットフォーム
  - ◆ Android / iOS

Capability

Sensors	Acceleration	±2/4/8/16G
	Gyro	±250/500/1000/2000 dps
	Magnetism	±4800μT
	Resolution	16bits
Wireless	Bluetooth Low Energy 4.2	
Rate	Up to 300Hz (Android)	
Battery	10 Hours	
LED	Status Indicator	
Button	Power Control	
Connector	Micro USB	
Size	28mm × 24mm × 11mm (with Case)	
Weight	7.7 grams (with Case)	
Application	Mobile App / Database / Desktop	
SDK	iOS / Android / C#	

ユースケース

- ➔ 高齢者の行動検出アプリ
  - ◆ 転倒検知や生活習慣の可視化
    - ● センサーでのモーションサンプリング
    - ● 機械学習を使った動作検出

ユースケース

➔ 複数のセンサーを組み合わせ、3Dオブジェクトを動かす。

補足資料

- 連携している研究室で以前に公開した論文

厳密には同じ状況（今回想定しているものとはセンサーの個数が違う）ではないのですが、こういった研究の実績があります。

2017 IEEE International Conference on Systems, Man, and Cybernetics (SMC)
Banff Center, Banff, Canada, October 5-8, 2017

Recognition of Daily Routines and Accidental Event with Multipoint Wearable Inertial Sensing for Seniors Home Care

Lei Jing and Zixue Cheng
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***Abstract*—Human Activity Recognition (HAR) is a critical technology for seniors home care. In this paper, we present the system implementation and experimental study on detection of both of the daily activities and accidental event (Fall Down) with multiple inertial sensors on body. The overall accuracy are 94.3% on recognition of 10 kinds of daily activities with kNN in user-independent evaluation. Moreover, the experiment shows that the combination of multiple sensors on different locations of upper, middle, lower body parts can improve both of the accuracy and stability (one node: 78.1%±8.0%, two nodes: 90.8%±4.7%, and three nodes are 94.3%±4.4%). Finally, we investigate the detection of fall down from the other ten daily activities. The accuracy is 87.5% with mean and standard deviation as the features, and improved to 100% with energy as the additional feature.**

I. INTRODUCTION

Home care will act an important role for the senior citizens. Taking Japan as an example, senior citizens (over 65 year old) are about 26.7% of total population by 2016, and more than 40% senior citizens hope to take home care instead of living in the nursing home [1]. And the number is increasing year by year because of the reduction in mortality, low birthrate and longevity.

Automation and personalization of home care system are the future trend since the shortage of manpower and requirement of improving the Quality of Life (QoL). On one hand, the number of people engaged in the nursing care is decreasing, and the situation involving the shortage of manpower supply in the nursing care field is getting more and more serious. For these reasons, it is difficult to manage the healthcare of all elderly people living alone manually. On the other hand, people realize the importance to prolong the healthy life, and hope to get personalized and timely home care and medical services. One example is a system that can detect the initial symptoms of diseases that elderly people are prone to, such as Parkinson's disease. Another example is a system that creates a life log of elderly people by recognizing their daily movements, which enable the family doctor to provide accurate medical service. Therefore, the development and dissemination of such a system is urgently needed for managing the healthcare.

Environmental sensing and on-body sensing are two kinds of technologies for recognizing actions according to the placement of the sensing devices. On one hand, environmental sensing systems fix the sensors in the surrounding environment to detect the body movement relative to the surrounding. The optical, audio, thermal sensors are often adopted in such system. Such systems features as higher accuracy raw data and no requirement of on-body device. But they show poor mobility and prone to dead end problem. On the other hand, on-body sensing systems directly set the sensing devices with the detection target. The inertial and magnetic sensors are often adopted in such system. Such systems feature as high mobility, independent to the environment. But the raw data accuracy is lower and users need to take the sensing devices with them.

As a summary, environmental sensing are proper for long-term monitoring on a fixed point for one user. For example, camera studio motion capture system is widely used for the film production, which even can capture the actor's facial expression. However, the intrinsic constrains, like fixed space, dead ends, and high cost, prohibit it to be widely spread in the daily life environment. Meanwhile, on-body method is independent to the environment and low cost for deployment. Therefore, it would be more proper for daily life HAR if we could improve the recognition accuracy and stability out of the low accuracy raw data.

In this paper, we propose a multipoint wearable monitoring system that can not only automatically record and recognize the periodic daily activities, but also can detect the sporadic emergency event to provide timely help to the seniors. The system detects daily routines such as walking and eating and dangerous movement like falling down, which may be an initial symptom of Parkinson's disease. Also, because the wearable sensors to be used are small and lightweight, they can keep on detecting daily actions for a long term. Ultimately, the system contributes to improve the QoL of the seniors taken home care.

The application model of the proposed system is show in Figure 1. First, mount multiple inertial sensor nodes to the body to recognize daily movements. Next, create a life log based on the recognition result. Finally, it is provided to distant

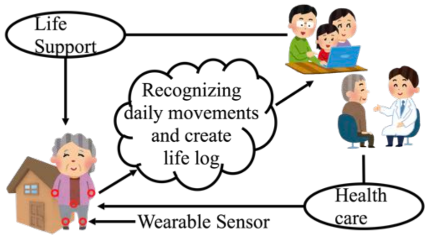

Fig. 1: Application model for seniors home care.

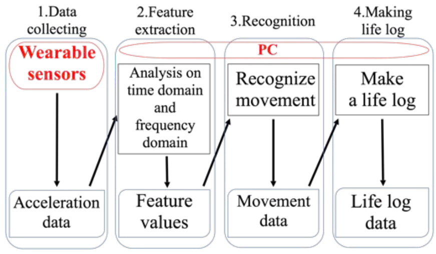

Fig. 2: System outline.

families and family doctors for assisting life and healthcare.

The contribution of this paper includes

- We propose a full function HAR system with originally designed wireless sensor nodes. The sensor offset and bias are calibrated and filtered to mitigate the sensing errors on the recognition. The sensor node is light weight and low energy for long term data collection. The data can be wireless transfer to the server with the BLE protocol.
- We investigate the system performance on different types of actions. Daily actions have compositional complexity and personnel difference. Therefore, we evaluate the system on a activity set including both of periodic, sporadic, and static actions. And user independent experiment is performed to evaluate the system stability.

II. Related Work

Human Activity Recognition (HAR) refers to automatic recognition of physical activities to allow computing systems to provide proactive service [2]. The recognition system can be divided into two categories according to the placement of the sensing device in the surrounding environment or on the user's body. Many researches investigated automatic recognition of gestures and activities from static images or dynamic videos in constrained environments [3] [4]. And body-worn HAR system is first studied during the late of 1990s. Currently, On-body sensing with accelerometers or gyroscopes is recognize as a promising technology to track activities in unconstrained daily life settings [5]. We introduce the related works surrounding three topics: sensing device, device placement, and activity definitions.

Some researches use commercial sensing device like Wii [6], pad, or smartphone [7] [8]. Such devices are not optimized for the HAR usage. The devices are bulky and obtrusive to be worn on body in real life. Moreover, as the third party, the HAR system developers lack of the sensor control including sampling rate control, sensor bias and offset control, etc. For example, on Nokia Symbian and Maemo phones, the sampling rate of accelerometer vary between 25˜38 depending on the CPU load [9], which have unignorable influence on the stability of the HAR system [7]. In view of this, a dedicated sensing node is designed for the HAR system in this paper. The sensor node is in the form factor of a finger nail. It is self-contained with a standard wireless TCP socket interface for data transfer. The highest priority is assigned to the sampling to ensure a stable sampling rate.

The recognition accuracy is closely related with the on-body placement of the sensing devices [5]. The sensors can be placed on many locations of the body like ear, neck, chest, upper arm, lower arm, wrist, finger, waist, hip, thigh, knee, ankle, foot, and so on. Paper [10] investigates the multi-sensor and single sensor HAR system with a garment involving four accelerometers. As the result, multi-sensor is about 5% outperform single sensor across 8 kinds of activities. But all the sensors are placed on the trunk of the body, the placement on the four limbs are not investigated. Paper [11] developed a HAR system to recognize 20 daily activities with 5 sensors on the whole body to achieve 84% overall accuracy. But it does not mentioned the data pre-processing like sensor offset calibration, and bias filtering. Therefore, it is desired to perform additional investigation on the multi-sensor HAR system with stable sampling rate and accurate data pre-processing.

In daily life, there are diverse routine activities and accidental events. Generally, they can be divided into three types: Periodic, Sporadic, and Static [2]. The periodically repeated activities are most widely investigated, like walking, running, eating, tooth brushing, vacuuming, typing, cycling, etc. [12] [13] [14]. The detection of some sporadic actions like fall down is discussed in several research [15] [16] [17]. Finally, some activities can be defined as a kind static postures like stand up, lie down, which are generally studied together with the periodic activities. So far, seldom research performs the evaluation on all three types of activities. However, it is desired for a HAR system for seniors home care to recognize all three types of activities.

III. System Design

A. System Outline

The recognition system consists of four steps as shown in Figure 2. First, acceleration and angular velocity data are collected from inertial sensors. Next, feature vector value are extracted from both of the time and frequency domain. Third, recognition of activities use k-Nearest Neighbor algorithm (k-NN). Finally, we make a life log based on the recognition results.

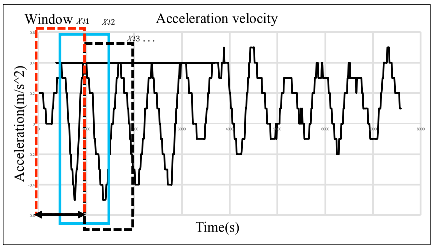

Fig. 3: Half overlap slide window with window size 64.

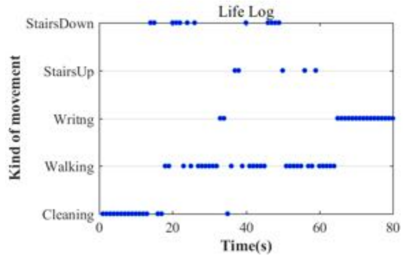

Fig. 4: Visual Lifelog Interface.

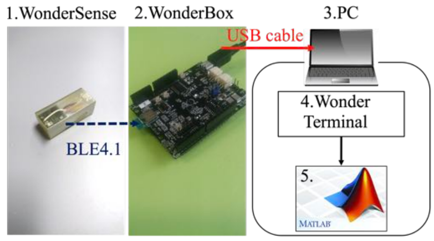

Fig. 5: Example of Lifelog display.

B. Data Collection

Multiple sensor nodes are worn on different body parts for data collection. In this research, we use a very compact motion capture sensor node named WonderSense (WS), which is developed in our laboratory and optimized for motion capture. Three dimension acceleration and angular velocity data can be acquired with WS node. Then the collected data are wirelessly send to a data server. The sampling frequency is set at 20Hz as a trade-off between the recognition rate and power consumption.

C. Feature Extraction

We use the half-overlapped slide window method over the sensor raw data to calculate the features (Figure 3). The window length (w) is fixed to 64. Therefore, length of one window is about 3.2 seconds.

We calculated three kinds of feature values, which are mean (1), standard deviation (2), and energy (3) based on the acceleration data. Mean and standard deviation are calculated on each axis. Energy is obtained by performing Fast Fourier Transform (FFT) on the acceleration of each axis. The definition of each feature is listed below for a given signal $X_n = \{x_1, \cdots, x_w\}$. X_n is the set of data contained in the n-th window. In addition, F_i is the i-th component of the Fourier Transform of X_n.

$$\overline{x} = \frac{1}{w}\sum_{i=1}^{w} x_i \tag{1}$$

$$\delta_x = \sqrt{\frac{1}{w-1}\sum_{i=1}^{w}(x_i - \overline{x})} \tag{2}$$

$$Energy(x) = \frac{\sum_{i=1}^{w} F_i^2}{w} \tag{3}$$

D. Activity Recognition

We use k-Nearest Neighbor algorithm (k-NN) since it is frequently used for HAR, which makes it easier to compare this study with other studies. Learning data are plotted in the feature space in advance. If unknown data is obtained, we obtain k learning data in order from the closest Euclidean distance and estimate the class to which the data belongs by majority vote. Two feature set are defined for recognition of daily routines and fall down respectively. The first feature vector includes mean and standard deviation of acceleration ($f_1 = \{m_x, m_y, m_z, sd_x, sd_y, sd_z\}$). The second feature vector includes mean, standard deviation, and energy of acceleration ($f_2 = \{m_x, m_y, m_z, sd_x, sd_y, sd_z, e_x, e_y, e_z\}$).

The representative training samples are selected by k-means method to improve the system stability and reduce the computation cost. For each kind of activity, ten training data, which are closer to the k-means center of all samples, is picked up as the training data.

E. Visualization

Users can check their life log through a visual graph as shown in Figure 4. Horizontal axis represents the time, and vertical axis represents the different activities. One marker represents 3.2 second of the recognized movement in the graph.

IV. System Implementation

Figure 5 shows an overview of the experimental system. Acceleration data obtained from WonderSense are sent to the PC via a hub device named WonderBox (WB). Next, WonderTerminal running as a server passes the collected data to MATLAB for feature vector calculation and action recognition. Finally, both of the recognized results and raw data are stored in the text files.

This section describes the hardware and software used in this system.

1) WonderSense (WS) is a very compact, self-contained sensor node with BLE interface.
2) WonderBox (WB) can have at most eight WSes at the same time with maximum 50Hz sampling rate.
3) The feature calculation and recognition parts are implemented on a PC. We set up this part with three kinds of

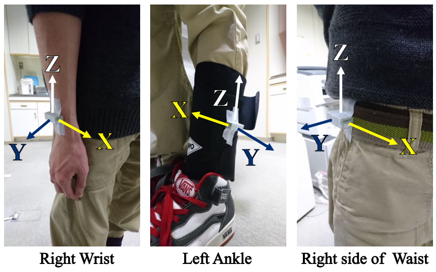

Fig. 6: Position and direction of each sensor node on wrist, ankle, and waist.

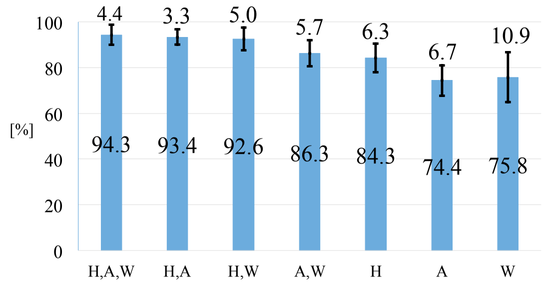

Fig. 7: Accuracy and standard deviation for each nodes combination. (H: right wrist, A: left ankle, W: waist)

different operation system: Microsoft Windows, Mac OS, and Linux.

4) WonderTerminal (WT) can work as a server with a well-defined packet format.
5) MATLAB is used for recognizing daily movements and generate a graph of life log. The raw data and recognized data are stored in the text files.

V. Evaluation

We examined the accuracy of this system on both of the daily activity and accidental event.

A. Activity definition

Totally, eleven kinds of actions (Ten daily activities and one accidental action (Fall down)) are tested in the evaluation experiment. Specific action name and definition of each activity is given in Table I.

B. Experiment conditions

Experiment condition settings are described in Table II. Both of daily movement and accidental event are tested in the experiment. For each daily movements of No.1 to No.10 in Table I, we acquired data in two sections for each type of movement. The first section was used as training data, and the second section as testing data. Each section was about 60 seconds and it did not include any other types of movement.

Regarding No. 11, falling down, we acquired the data for each direction in three sections. Each section is about 60 seconds. The data acquired for the first and second section were used as training data, the third section as the testing data. To investigated whether falling down could be detected from the other activities, we ask the subjects to do some daily movement like walking around, seat down, or stand up, and fall down. Also, it is difficult for a subject to fall down incidentally, so this action was recognized only when it was consciously done.

C. Sensor node position

Figure 6 shows the wearing position of each sensor node. The sensors were mounted so that its Z axis was upward in the opposite direction of the earth gravity when the subject was upright.

D. Results and Discussion

1) Overall recognition rate on daily activities: The recognition accuracy is investigated for the ten kinds of daily activities with three sensor nodes using k-NN method (k=5). The results for the six subjects are summarized in the confusion matrix (Table III). The numbers in the table are the number of windows generated from the sensor raw data. For example, for "8.Walking," the input raw data were divided into 174 windows. As a result, 173 of them were Truth Positive correctly recognized. However, 1 window was erroneously recognized as "2.Going down stairs." Finally, the overall recognition rate was 94.3%. Especially, 21.8% of "5.Resting in chair" is incorrectly recognized as "10.Writing", since both of them featured as the same static pose for the sensor on the ankle and waist and dynamic action on the wrist.

2) Node position VS accuracy for daily activities: We divide the human body into three parts (upper, middle, and lower) to investigate the relationship between different location combinations with accuracy and stability. Figure 7 shows the results on the ten kinds of daily activities in this experiment setting. We achieved the best result (94.3%±4.4%) when subjects worn nodes on all three locations. Only one node on ankle get the worst result (74.4%±6.7%). The average performance for one node is 78.1%±8.0%, two nodes are 90.8%±4.7%, and three nodes are 94.3%±4.4%. Therefore, wearing more nodes on different locations of upper, middle, and lower body parts can increase the accuracy and stability. Meanwhile, two nodes combinations are a kind of tradeoff between the performance and cost. Especially, the wrist and ankle combination (H, A) is only about 1% less than the best result.

Moreover, the three locations show different contributions on recognizing the ten kinds of daily activities. The contribution refers to the improvement in the accuracy with every additional sensor node. The quantitative definition of the contribution is given in Formula V-D2. According to the Formula V-D2, we can get the contribution of each location in Table IV. The node on wrist (C_H: 19.0%) is more than two times of contribution than the other two locations (C_A : 8.8%, C_W : 8.9%). Because featured patterns can be found in almost

TABLE I: Actions Evaluated in the Experiment

ID	Action type	Action name	Definition of each action
1	Daily Activities	**Tooth Brushing**	Clean the teeth with a manual tooth brush
2		**Going Down Stairs**	Going down the stairs
3		**Eating**	Eat meals with a spoon
4		**Lie Down**	Body in the horizontal flat position
5		**Resting**	Sitting in a chair without making a large motion
6		**Going Up Stairs**	Climb up the stairs
7		**Clean Up**	Clean room with a vacuum cleaner
8		**Walking**	walk around
9		**Washing Face**	Wash face with two hands
10		**Writing**	Write characters with a pen on paper
11	Accident Actions	**Fall Down**	Fall down to the four directions while walking or stand up

TABLE II: Experiment Conditions

Action type	No. Activities	Sampling rate	Section duration	No. Sections	No. subjects	No. Nodes	No. data	Handed-ness	Node positions	Feature values
Daily activities	10	20	60 seconds	Training: 1 Testing: 1	6 (3Female, 3 Male)	3	Training: 216,000 Testing: 216,000	Right	Right wrist, Left ankle, Right side of waist	Mean, Standard deviation
Accident actions	Fall down in 4 directions	20	60 seconds	Training: 2 Testing: 1	2 (2 Male)	3	Training: 28,800 Testing: 14,400	Right	Right wrist, Left ankle, Right side of waist	Mean, Standard deviation, Energy

TABLE III: Overall Recognition Results

Accuracy 94.3		Predicted 1	2	3	4	5	6	7	8	9	10	Recall (%)
Actual	1. Tooth Brushing	168										100
	2. Going Down Stairs		91						1			98.9
	3. Eating	3		152		1				6	6	90.1
	4. Lie Down				168							100
	5. Resting in Chair					133					37	78.2
	6. Going Up Stairs		3				91		4			92.9
	7. Clean Up		1					173				99.4
	8. Walking		1						173			99.4
	9. Washing Face	18		2				1		147		87.5
	10. Writing			1							167	99.4
Precision(%)		88.9	94.8	98.0	100	99.2	91	99.4	97.2	96.1	79.5	

all the daily activities, like “1. Tooth Brushing”, “3. Eating”, “7. Clean Up”, “9. Washing Face”, “10. Writing”, and even for the activities without intentional movement on the hand, like “2. Going Down Stairs”, “4. Lie Down”, “5. Resting in Chair”, “6. Going Up Stairs”, “8. Walking”.

$$C_x = \sum_{i=1}^{3} C_{x_i}$$
$$and,\ C_{x_i} = \frac{\mathrm{R_{x+y}} - \mathrm{R_x}}{\mathrm{R_x}}$$

where, $(x, y \in \{H, A, W\})$, and R is the recognition rate.

3) Detection of accident action: When we use only mean and standard deviation as feature value, the accuracy on “11. Falling Down” is about 87.5%. When Energy as new feature is added to feature value, the accuracy becomes 100% (Figure 8).

Comparison study of Energy waveform is investigated on both of daily activities and accident action. Figure 9 shows the average energy waveform of the z-axis of the waist sensor node. Seven continuous windows (about 22 seconds) are picked up from both of five kinds of daily activity data and fall down data to take a comparison on the waveform of the energy. When the subjects performed daily movement, the energy waveform keeps at a constant value as the upper curves in Figure 9. On the other hand, when the subjects fell, the energy waveform dropped significantly regardless of the falling direction. The same features could be observed on the other nodes as well. Therefore, Energy could be an efficient feature to detect the Fall Down from daily activities.

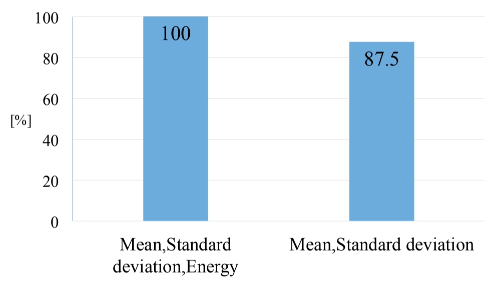

Fig. 8: Comparison of accuracy on Fall Down detection with or without energy feature

4) Subjects’ feedback on the usability: Finally, we asked each subject about his/her impression at the end of the experiment. All subjects feel that the system can be practically

TABLE IV: Contribution of the Three Different Location on Body

Node Comb	Rate %	Node Comb	Rate %	Node Comb	Rate %	Node Comb	Rate %	Node Comb	Rate %	Node Comb	Rate %	Node Comb	Rate %	Node Comb	Rate %	Node Comb	Rate %
A	74.4	W	75.8	AW	86.3	H	84.3	W	75.8	HW	92.6	H	84.3	A	74.4	HA	93.4
A+H	93.4	W+H	92.6	AW+H	94.3	H+A	93.4	W+A	86.3	HW+A	94.3	H+W	92.6	A+W	86.3	HA+W	94.3
C_{H1}	25.5	C_{H2}	22.2	C_{H3}	9.3	C_{A1}	10.8	C_{A2}	13.9	C_{A3}	1.8	C_{W1}	9.8	C_{W2}	16.0	C_{W3}	0.9
C_H	19.0					C_A	8.8					C_W	8.9				

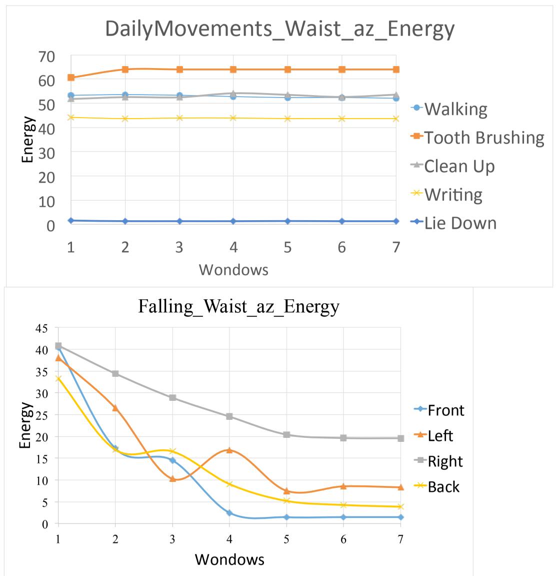

Fig. 9: Energy waveform of the sensor node on the waist (z axis)

applied in daily environment since the sensor node is very compact and not worry to hinder the daily activities. Some people also pointed out that it is not so convenient to carry an additional hub device for data collection.

VI. Conclusion

In this paper, we proposed, implemented and evaluated a system to recognize both of the daily activities and accident actions with multiple wearable sensors on the body. The experiment shows that combination of multiple sensors can achieve higher recognition accuracy. Moreover, Energy could be an effective feature to identify the accident action like Falling Down from the daily activities. In the next step, we will invite more subjects to use the system in their routine life to verify the above claims.

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