Monitoring Bed Activities via Vibration-Sensing Belt on Bed

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***Abstract*--The aging issue has become an important issue of the world, mostly because the aging body makes elderly people in high risk. Since falling is a common accident when getting off bed and bed activities can help estimate sleeping quality, it is desirable to monitor bed activities for elderly people sleeping on beds. In addition, the deployment should be simple for the practicability. In this work, a simple vibration-sensing belt is deployed on the bed to collect signals about how users interact with the bed, and corresponding algorithm is developed to analyze signals for monitoring bed activities for users.**

I. INTRODUCTION

The substantial leap in medical technology increases the average life expectancy, thus leading to an aging population. Because the aging body makes elderly people in high risk, great efforts are required for their family members and caregivers to take care of elderly people. Unfortunately, not only the professional caregivers are in shortage, but also the busy working makes this responsibility a sweet burden for modern mid-age people. However, as the technology of IoT (Internet of Things) becomes mature, it is popular to build "smart care homes" based on IoT as care resources[1], so as to provide the foundation to take care of elderly people, and in turn, to relieve the burdens of caring elders for modern people.

This work focus on applying simple IoT to beds for monitoring users' bed activities. The primary reasons are: 1) falling is a common accident when elderly people get off bed, and this accident may result in serious consequences; 2) bed activities can help estimate sleeping quality, which is a useful health information; and 3) simple IoT can reduce the barrier of technology and cost, and thus enhance the practicability.

II. SENSING MATERIALS

The adopted sensing material is a vibration-sensing belt, which is a kind of piezoelectric sensor [2] with belt shape, deployed on the bed as shown in Fig. 1. After collecting signals about how users interact with the bed, data are transmitted to a computer for further analysis, so as to detect bed activities.

This sensing material is highly sensitive to the change of force being applied. The raw data readings from this sensing material corresponding to several kinds of bed activities (getting on bed, getting off bed, flip on bed) is shown in Fig. 2.

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When users undertake bed activities applying force to the deployed sensor, the raw data readings change significantly. Moreover, observed from the enlarged diagram at the top right part of Fig. 2, there is a constant little vibration when users on bed. This little vibration results from the force applied by the vital signs of human body (e.g. heartbeat, respiration). In another word, the signals resulting from the interaction with humans are very similar to the one used in previous works related to health monitoring based on vital signs.

III. ALGORITHM

Based on the observation from Fig. 2, the algorithm for monitoring bed activities is developed as Fig. 3 and illustrated below: 1) build a background model to describe the raw data readings for nobody on the bed; 2) use the background model to estimate the vibration strength so as to identify whether there is a user on the bed; and 3) estimate the level of force changes so as to detect whether users undertake bed activities.

A. Background Model for Nobody on Bed

When there is nobody on the bed, the raw data readings are only effected by environmental noisy signals, and the values are continuously varying within a near-to-zero range. However, this varying range depend on surrounding environment, so rather than a fixed value, the background model needs an adaptive way to find the reasonable varying range of raw data readings when nobody on bed.

The adopted feature is second central moment (i.e., the average variance) of raw data readings within recent 1 second. The feature for the *i*-th data sample is denoted as $f^{(i)}$ and calculated as follows, where h is the number of samples per second (e.g., h=40 for 40 Hz sampling rate).

$$f^{(i)} = 2^{nd}CentralMoment\{x^{(i)}, x^{(i-1)}, \ldots, x^{(i-h+1)}\}=\Sigma(x^{(i)}-\bar{x})^2$$

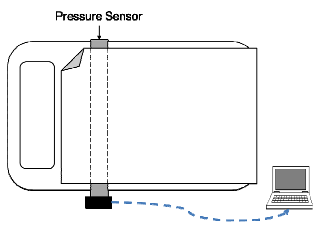

Fig. 1. Deployment of the vibration sensor as sensing belt on bed.

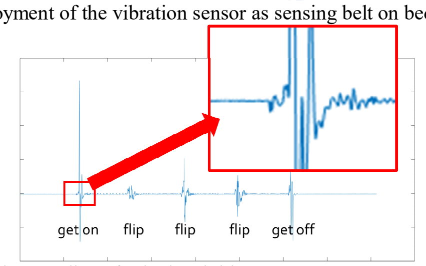

Fig. 2. Raw data readings for bed activities.

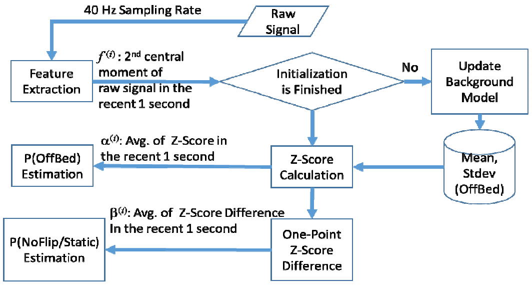

Fig. 3. Algorithm flowchart for bed activities.

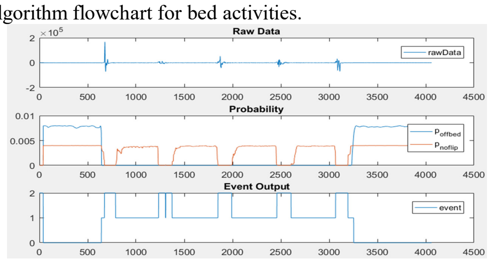

Fig. 4. Experimental results for bed activities of subject 1.

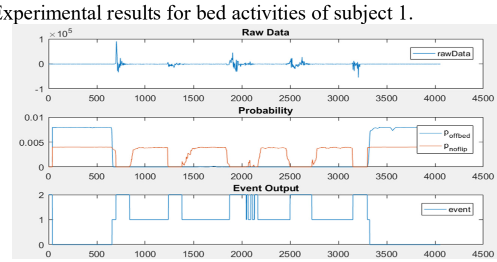

Fig. 5. Experimental results for bed activities of subject 2.

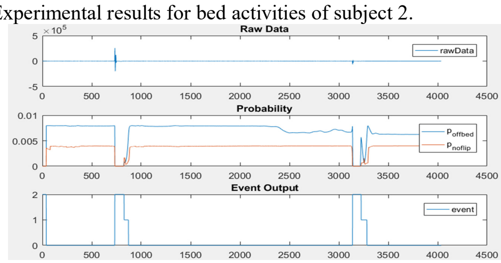

Fig. 6. Experimental results for bed activities of dummy subject.

The background model is denoted as (μ_B,σ_B), based on the feature values collected for t seconds when nobody on the bed.

$$\mu_B = Avg\{f^{(0)}, f^{(1)}, \ldots, f^{(h*t-1)}\},\ \sigma_B = Stdev\{f^{(0)}, f^{(1)}, \ldots, f^{(h*t-1)}\}$$

B. Estimation for Nobody on Bed

Provided with the background model (μ_B,σ_B), z-score for the i-th data sample can be calculated as $z^{(i)}=(f^{(i)}-\mu_B)/\sigma_B$, which represents the normalized distance to background model:

Estimation for nobody on bed is based on average z-score within recent 1 second, $\alpha^{(i)} = (z^{(i)}+z^{(i-1)}+\ldots+z^{(i-h+1)})/h$

Assumed that the behavior of $\alpha^{(i)}$ follows a normal distribution (μ=0,σ), the corresponding probability density of $\alpha^{(i)}$ can determine whether users on the bed given a threshold value th_{offbed}. In this work, σ=10 and th_{offbed} =0.006.

If $P_{offbed}(\alpha^{(i)}) > th_{offbed}$ then nobody on bed, otherwise users on bed, where $P_{offbed}(\alpha^{(i)})=\frac{1}{\sigma\sqrt{2\pi}}e^{\frac{-(\frac{\alpha^{(i)}-\mu}{\sigma})^2}{2}}$

C. Estimation for Bed Activities

As shown in Fig. 2, bed activities result in significant irregular vibration due to significant force changes. Provided with $z^{(i)}$ of each data sample, 1-point z-score difference is calcualted as $\Delta z^{(i)}=|z^{(i)}-z^{(i-1)}|$, the level of force changes.

Estimation for bed activities can be based on average $\Delta z^{(i)}$ within recent 1 second as $\beta^{(i)} = (\Delta z^{(i)}+\Delta z^{(i-1)}+\ldots+\Delta z^{(i-h+1)})/h$

Assumed that the behavior of $\beta^{(i)}$ also follows a normal distribution (μ=0,σ), a threshold value th_{static} can determine whether users undertake some bed activities. In this work, σ=20 and th_{static} =0.0001.

If $P_{static}(\beta^{(i)}) > th_{static}$ then no bed activities, otherwise users undertake some bed activities (getting on/off bed, flip on bed).

D. Experimental Results

Two human subjects (188cm/75kg and 171cm/85kg) and one dummy subject (a pile of A4 paper, 12kg) are involved to verify the developed algorithm. During the 90 seconds experimental period, subjects get on bed at the 15-th second, and get off bed at the 75-th second. Two human subjects change their poses every 15 second when on bed.

The experimental result is shown in Fig. 4~6, where (0=NotOnBed, 1=OnBed, 2=Flip) in the event output. The developed algorithm not only successfully detects bed activities for two human subjects, but also identifies that the dummy subject is not a human on bed. This can further help monitor whether the vital signs of elderly people disappear during their sleep, so as to inform family members or caregivers to enable emergency aid ASAP when necessary.

IV. CONCLUSION

In this work, a simple vibration-sensing belt is deployed to sense the interaction between users and beds, and an algorithm is developed to detect the sensed bed activities. Elders' bed activities can thus be monitored easily, and then for their family members or caregivers to provide help when necessary. Comparing with other systems based on pressure sensors [6] or camera [7], this proposed system has comparable performance but with easy deployment whereas no privacy issues.

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