Pedestrian Detection with High Resolution Inertial Measurement Unit

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***Abstract*—Inertial sensors are used widely for detecting different contexts. However, noise components at high frequencies can disturb the recognition. In this paper, the measurements are made with multi IMU (MIMU) which combines the results of 32 inertial sensors. Averaging of individual sensor outputs reduce the noise level significantly and enables higher resolution. As an example case, we present application for passenger detection in two environments; hallway corridor and public city bus. The results show that accuracy can be increased when MIMU is used compared to single IMU.**

***Keywords*—inertial measurement unit, multi inertial measurement unit, MEMS, IMU, MIMU, pedestrian detection.**

I. Introduction

Nowadays, small MEMS inertial measurement units (IMUs) containing accelerometers and gyroscopes can be found almost everywhere and there exist multitude of applications that are using information from those sensors. However, for some applications the noise levels of these sensors can be too high. One example is calculating number of pedestrians using floor attached IMU with vibration analysis. This is an applicable problem in public transportation.

The knowledge of number of passengers is an important information in design and maintenance of public transportation systems. Especially it is important to be able to estimate the passenger number automatically in intelligent transportation systems (ITS). Different technologies have been used previously for passenger number estimation in public buses, e.g., pressure sensors [1], [2]. In addition, camera based systems for pedestrian detection are widely used [3]. Conventionally, body mounted or hand held IMUs are used for detecting the steps of a pedestrian [4]. However, to the authors' knowledge, there exists no prior work for passenger estimation with floor attached IMUs. Unlike camera and pressure sensor based systems, IMU based system can also bring some additional information. For example, accelerations and deaccelerations, i.e., driving behavior, as well as road conditions like bumps and road can be obtained [5], [6].

In this paper, we study the possibilities of using inertial sensors for estimating number of passengers in public city bus. We present measurements made in an office corridor and in traditional diesel city bus. Office corridor measurements are used as baseline without additional disturbances like vibrations in real vehicles. Electric buses have less vibrations than diesel buses due to missing combustion engine, i.e., the corridor measurement can be used – at least partially – to simulate the situation when electric bus is in a bus stop. Measurements from the public city bus, i.e., diesel bus, are made to get data from real bus in a traffic. In this case, there is a lot more vibrations than in electric bus. This means that if we are able to recognize passengers in diesel bus, we will most definitely be able to do it in electric buses. In this paper, we present preliminary work for passenger number estimation in hallway corridor and public city bus. The measurements in this paper are done with Multi Inertial Measurement Unit (MIMU) which is an open-source inertial measurement unit (IMU) containing 32 commercial grade sensor chips. This reduces the noise level significantly and leads to more accurate results. The results indicate that accuracy can be increased vastly when MIMU is used compared to single IMU. In short, our contributions in this paper are

- Passenger detection in city bus using floor attached IMU
- Accuracy improvement in such a system using multi IMU

The remainder of this paper is organized as follows. In section II measurement device is introduced. Section III concentrates on detecting basic walk and passengers entering to traditional diesel city bus with a IMU attached to the floor. Section IV makes the conclusions and gives guidelines for the future work.

II. Measurement Device

Measurement device used in this paper is an open-source IMU containing 32 commercial grade sensor chips. The IMU is advanced version of IMU presented in [7]. The used MIMU4444v1 can be seen in Fig. 1 Each sensor chip contain 3-axis accelerometer and 3-axis gyroscope. The advantage of using multiple sensors, i.e., averaging the sensor values, is that the effect of noise can be substantially reduced. This can be clearly seen from Discrete Fourier Transform (DFT) in Fig. 2 where the IMU was stationary on table. The noise level of combined signal is $s_c = s_1/\sqrt{n}$ where s_c is noise level of combined signal, s_1 is noise level of one sensor, and n is number of sensors combined.

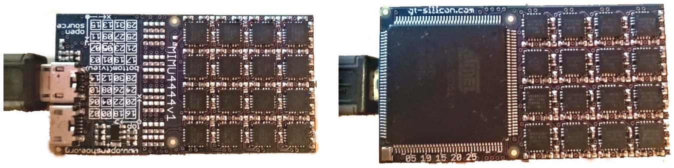

Fig. 1. Multi Inertial Measurement Unit MIMU4444v1

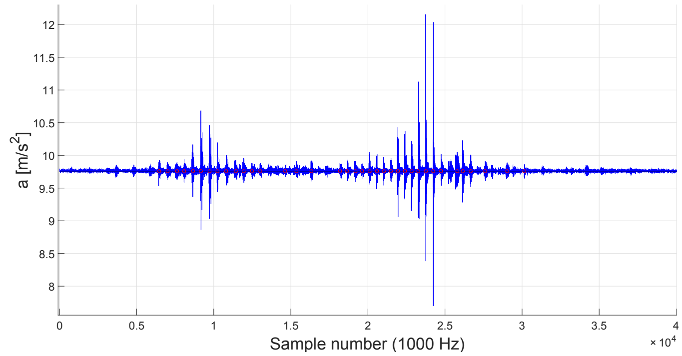

Fig. 3. Vertical axis acceleration signal from people walking on corridor and the detected steps

III. Pedestrian Detection

A. Detecting Walk in Corridor

Detecting walking persons in an office corridor is the easiest situation to start with in developing algorithms for passenger recognition as there are no disturbing vibrations. Step detection of a pedestrian have been previously done a lot in waist- or torso-mounted pedestrian dead reckoning (PDR) systems like in [4]. However, the situation is totally different when the sensors are attached to the platform where people are walking.

We made measurements with MIMU attached to the corridor floor made of plywood boards. This floor type were chosen for the tests as the floors of city buses are also made of plywood. Fig. 3 shows the z-axis, i.e., vertical axis, acceleration when people are passing the sensors on the corridor from one data set. The detected steps are shown in the figure as red circles.

B. Passenger Detection in Traditional City Bus

Detecting walking passengers is much harder task to do with accelerometers in city bus due to additional vibrations compared to corridor. The strongest individual component of vibration in traditional city bus is the diesel engine. Because of that, we can assume that if we are able to recognize the movement of passengers in a diesel bus, we can make it also in an electric bus.

At this stage, we concentrated on recognizing the passengers entering the bus via the front door as a typical entry point. At first, we have to be able to recognize when the bus is stationary, as in reality, this is the only time when passengers may enter the bus. The bus can be stationary in multiple situations, e.g., in traffic lights and bus stops. Thus, it is necessary to be able to classify these situations. It is relatively easy to detect when the bus is stationary by analyzing the variances of accelerometer signals.

One way to find whether the passenger is walking in to the bus, is to use frequency domain analysis of the inertial sensors. As we know, the normal stepping frequency during walking is around 1.8 Hz [8]. Thus, if the measured data contains frequencies around 0.5 to 3 Hz, it can imply that there is pedestrian walking. To verify this, data sets from the traditional city bus were collected. Measurement device was attached to floor near front door of the bus. Upper picture Fig. 4 shows frequency domain magnitude response from the data when the bus was stopped in the traffic lights and, similarly, the bottom one illustrates magnitude response when the bus was in a bus stop and people were walking in to the bus from front door. It can be seen that there is clear peak in the walking frequencies in the latter picture.

As the frequency domain contains information whether people are walking in to the bus, also a classifier was trained for this purpose. For the features we used variance of each axis

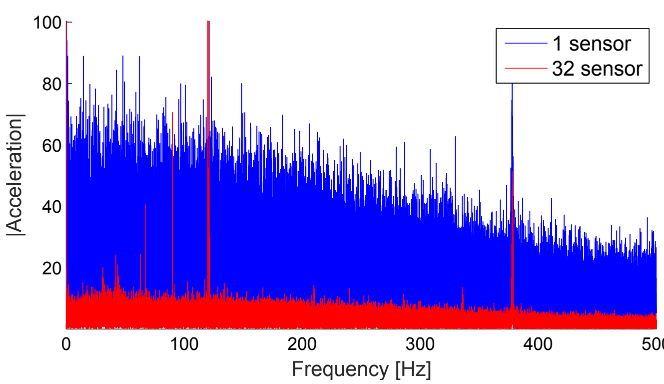

Fig. 2. DFT of 1 sensor vs. 32 sensors

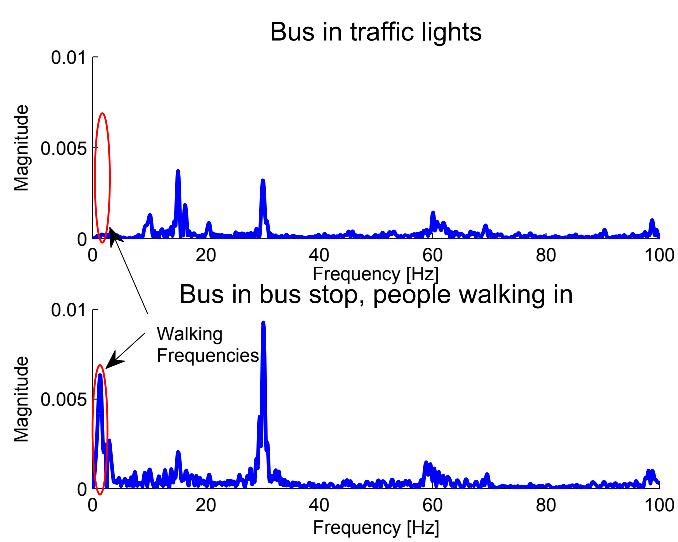

Fig. 4. Magnitude response of vertical accelerometer, when the bus was in traffic light (up) and a bus stop and people were walking in (down)

TABLE I
NUMBER OF CORRECTLY CLASSIFIED STATES USING MIMU AND SINGLE IMU

Features	Sensor	drive	stopped, no walking	stopped, walking in bus
DFT and variance of 3D accelerometer and vertical gyro	MIMU	98.7%	97.2%	61.3%
	IMU	97.5%	86.1%	77.5%
DFT and variance of Vertical (z-component) accelerometer	MIMU	90.8%	97.2%	79.4%
	IMU	97.0%	75.0%	46.9%

of accelerometer and gyroscope and magnitude response of the 512 long DFT of each accelerometer and vertical gyroscope. Naturally, if we are using computationally limited platform, the frequencies could be divided more sparsely (instead of full 512 long DFT). For example, only two bins could be used as a features; sum of the magnitudes under 4 Hz and sum of magnitudes of over 4 Hz. However, in this phase we wanted to use all the information possible.

Two different bus rides were used to train and evaluate classifier. The first bus ride with manual annotations were used to train a classifier and second bus ride was used to test the performance of the classifier. We trained a tree classifier using Matlab's ClassificationEnsemble AdaBoostM2 [9] with 1000 learners with the following states

- *drive*, a bus was driving normally
- *stopped, no walking*, a bus was stopped, but people were not walking in to the bus (this happened, e.g., in traffic lights).
- *stopped, walking in bus*, a bus was stopped in a bus stop and people were walking in from the front door of the bus.

The numerical results from the second bus ride is illustrated in Table I. Two different feature sets were used with both MIMU and single IMU. First feature set includes DFT and variance of 3D accelerometer and vertical gyro and second set has only DFT and variance of from vertical accelerometer. It can be clearly seen that MIMU over performs the single IMU in classification accuracy. Under 90 % accuracy can be seen with MIMU only with walking state. Lower accuracy in this case is partly explained by our manually annotated truth data, where in fact the people were not actually walking all the time but, e.g., stopped paying the bus fee. Authors acknowledge that these results are based on only one data set and selecting the features is not optimal. Thus, presenting very accurate classification results is not feasible. However, the results indicate, that pedestrian estimation using floor attached IMU is possible and, in addition, MIMU can over perform the single IMU in this kind of situations.

IV. CONCLUSIONS AND FUTURE WORK

The demonstrative purpose of this research is to be able to count the passengers in electric city bus with IMU. For now, we have been able to recognize walking pedestrian on office corridor made of plywood boards which depicts the situation when a passenger is walking on corridor of electric bus when it is on bus stop.

With traditional diesel bus, we were able to classify situations when the bus is moving and when it is stopped. And which is more important, when bus is stopped we were able to recognize when passengers are entering the bus with only few misclassifications. In addition, the results show how MIMU can over perform the single IMU in this kind of situations.

The next step in this research will be installing the sensors to electric bus and run thorough test campaigns with different application use cases. We are going to study also in which places the sensors should be attached in order to get the best results for counting the entering and leaving passengers. Packaging of multiple sensors to the same circuit board may cause cross-talking between gyroscopes. This may affect to the results and it will be investigated also in the future. Additionally, we are going to perform vibration analysis in order to detect road conditions. User experience is investigated to connect these measurements to passenger ride comfort.

ACKNOWLEDGMENT

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