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Optimal placement of IMU sensor for the detection of children activity

1st Magdalena Madej
Biomedical Engineering Department
Gdańsk University of Technology
Gdańsk, Poland
magdalena.madej@pg.edu.pl

2nd Jacek Rumiński
Biomedical Engineering Department
Gdańsk University of Technology
Gdańsk, Poland
jacek.ruminski@pg.edu.pl

***Abstract*—In this paper an investigation to determine the optimal placement of IMU sensors for the purpose of children characteristic activity detection is presented. The article compares four different placement of two IMU sensors on human body. Ten healthy volunteers participated within the study. Data were collected firstly from two wireless 9-axial IMU sensors placed at the left and right wrists, then sensors were placed at lower back and hip (dominant hand side). Activities included jumping, rotating, walking, walking on tiptoe, running, clapping hands, standing still, sitting still and dancing. Several parameters such as mean, standard deviation, skewness, kurtosis, energy, correlations, Hjorth parameters (activity, mobility and complexity) and spectra purity index, were calculated from measured data. Data from all locations provided similar levels of accuracy in differentiate analyzed activities.**

***Index Terms*—activity recognition**

I. Introduction

The measurement of parameters that allow to estimate children physical activity plays an important role in the assessment of various developmental disorders [1]. The level of physical activity as well as the presence of certain repetitive behaviors changes with the child's psychophysical condition. Currently, in most cases, the assessment of the child's behavior is based on the observation of caregivers, filling in questionnaires or using one of smartphone applications available on the market. Parents and teachers observations are usually taken in specific conditions that may have a bearing on the way the symptoms of the disorder are expressed [2]. Therefore, searching for objective measures may improve the assessment of the child's behavior. Automatic detection of children characteristic activities and automatic mobility assessment may help in a more objective evaluation of the child's condition [3]. Nowadays, devices with an embedded motion sensor, such as smartphones, smartwatches, smartbands and other standalone inertial measurement unit (IMU) devices are becoming very popular in physical activity research [4] [5] [6] [7]. The motion sensor can be a single accelerometer or combination of multiple inertial sensors: an accelerometer, a gyroscope and sometimes a magnetometer.[b8] The vast majority of motion analysis research is based on data from 3-axial accelerometer [9]. Data from 9-axial IMU (with accelerometer, gyroscope and magnetometer) provide an additional information about angular velocity and magnetic field that may be useful in some applications [10] [11] [12]. Motion analysis with IMU's has a very wide range of application e. g. physical activity pattern evaluation [13], tracking rehabilitation process [14] [15] , gait analysis [16] [17], supporting elderly in daily activities [18], sport science [19] or behavior analysis [20] [21]. When trying to characterize human behaviour and recognize different human activities the most common approach is to use machine-learning techniques [9] such as Bayesian decision making, the least-squares method, the k-nearest neighbour algorithm, dynamic time warping, support vector machines and artificial neural networks [11] [22]. To generate a predictive model that connects the raw IMU data with activity type using machine-learning algorithms the vector of features has to be defined. It can consist of time domain and frequency domain parameters [23] [24] [25].The most often recognized activities are sitting, standing, walking, running, lying and climbing stairs, that are global body motion activities. Several studies include also local interaction activities recognition, such as eating, hygiene activities, office activities and others [9].The most common motion sensor placement position are hip(waist), thigh, dominant wrist and dominant ancle. Non-dominant wrist or lower back placement is less popular [9]. For some purposes it is really important to enable the observed subjects to behave as naturally as possible, so the number and placement of sensors should be optimized. When observing children activities the sensors should be placed in a convenient and safe location. Based on our children observations wrists and lower back are the best choice, other sensors positions, like thigh, were find inconvenient when long wearing by examined child. In this research we try to find whether there is a significant difference in children activities recognition between non-dominant and dominant wrist sensor location and between lower back (preferable) and hip (most common) sensor location.

In this work, our contributions are as follows:

- We build a dataset of signals recorded from 9-axial IMU placed on 4 different locations. Recordings contain signals from 10 subjects performing 9 types of most often children activities, some of them, like walking on tip-toe, clapping hands or rotating are typical to children with specific developmental disorders.

- We propose a set of 35 parameters describing our data.
- As a result of experiments, we demonstrate that there was no significant difference between non-dominant and dominant arm and between lower back and hip placement of IMU when trying to differentiate between chosen activities.

The rest of the paper is structured as follows. In Section II, the methodology used in the study is described. The results are presented in Section III. In Section IV obtained results are discussed. The study is concluded in Section IV.

II. Methods

A. Experimental setup

The experimental setup consisted of two Mbient Lab Metamotions 9-axial inertial measurement unit (IMU) sensors with accelerometer, gyroscope and magnetometer used in recording mode. The range of gyroscope was ±2000st/s, the range of accelerometer was ±16g and the range of magnetometer was ±1300 uT. Sampling frequency for accelerometer and gyroscope was 100 Hz and for magnetometer 25 Hz. To obtain the synchronization between two IMU's all data were timestamped. Measured data were logged in build-in memory, then downloaded to mobile phone using MetaBase App and exported to a notebook computer . Together 10 volunteers, 3 women and 7 men were examined. Subjects ranged in age from 4 to 40 years (mean 23.8, sd ±14.4). Subjects wore two 9-axial IMUs at different locations on the body as shown in Figure 1: the first configuration where sensors are placed on wrists and the second where sensors were placed on lower back and hip from dominant hand side. These locations are typical sites where motion sensors are placed in activity recognition studies [24].

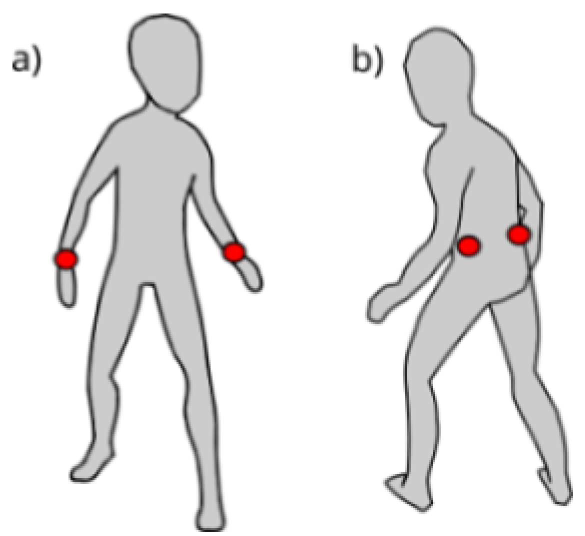

Fig. 1. Selected placement locations for the inertial measurement units. Configuration a) where sensors are placed on wrists and b) sensors placed on lower back and hip (dominant hand side)

B. Measurement procedure

Nine activities were studied. These consisted of typical children activities: 1-jumping, 2-rotating, 3-running, 4-walking, 5-walking on tiptoe, 6-clapping hands, 7-standing still, 8-sitting still, 9-dancing. All activities were maintained for a duration of 15 seconds then 5 seconds of standing still. There were two series of analyzed activities: the first with sensors placed on wrists and the second with sensors placed on lower back and hip. Data were manually labeled offline by an observer. Then 10 seconds of every activity were taken to analysis.

C. Methods of analysis

The purpose of the study was to determine whether there is a difference in physical activity assessment between a wrist-worn sensor at the dominant and non-dominant arm and between lower back and hip-worn sensor. Firstly, the raw acceleration, gyroscope and magnetometer data were labeled based on performed activity. Next,for each of nine activities, the vector v of 35 attributes extracted from each sensor was created, giving a total of 105 attributes for each IMU device. All features are presented in Table 1.

Before the analysis data were normalized. For each parameter the vector containing parameter values for every subject and every activity was centered and scaled to have mean = 0 and standard deviation = 1.

For one selected activity and one selected sensor from analyzed configuration a group of feature vectors $\mathrm{v}_{\mathrm{i,j}}$ (where i - activity, j - subject) for 10 subjects was selected.

Mean activity vector m_{i} consisted of 35 elements was calculated for each activity:

$$\mathrm{m}_{\mathrm{i}} = \frac{v_{\mathrm{i},1} + \ldots + v_{\mathrm{i},10}}{10}$$

Next, mean activity vector of selected activity was compared with 90 feature vectors of selected sensor (9 activities x 10 subjects) using euclidean distance between that vectors:

$$\mathrm{d}_{\mathrm{i,j,k}} = \| m_{\mathrm{i}} - v_{\mathrm{j,k}} \|$$

where: i - activity that is compared, j - activity that we compare with, k - subject.

Distance d was used to conclude whether the constructed feature vector allows to distinguish between the analyzed activities.

Next the euclidean distance d was averaged over subjects. Firstly, for each sensor separately, then for all sensors in selected IMU and configuration:

$$\mathrm{D}_{\mathrm{i,j}} = \frac{d_{\mathrm{i,j},1} + \ldots + d_{\mathrm{i,j},10}}{10}$$

III. Results

Calculated distances d for IMU placed on non-dominant wrist are presented on Figures 2 - 4. Maps of average distances from activity vector separately for each sensor for IMU's placed on both arms are presented on Figure 6. Minimum distances from activity vector, separately for each sensor when IMU's are placed on both arms are shown on Figure 7. Minimum distances from activity vector, separately for each

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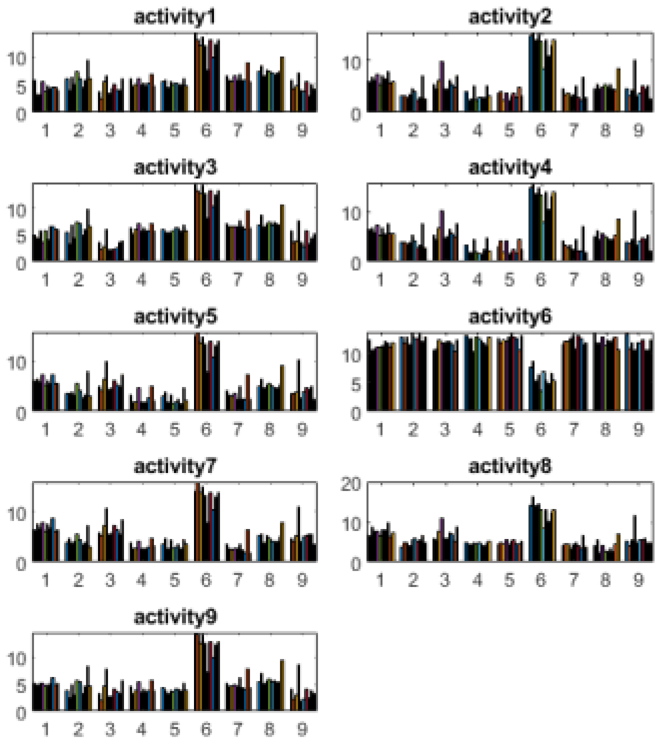

Fig. 2. Euclidean distance d (vertical axis) between mean activity vector and selected activity vector, for 9 activities and 10 participants, grouped by activities (horizontal axis), IMU placed on non-dominant arm, accelerometer

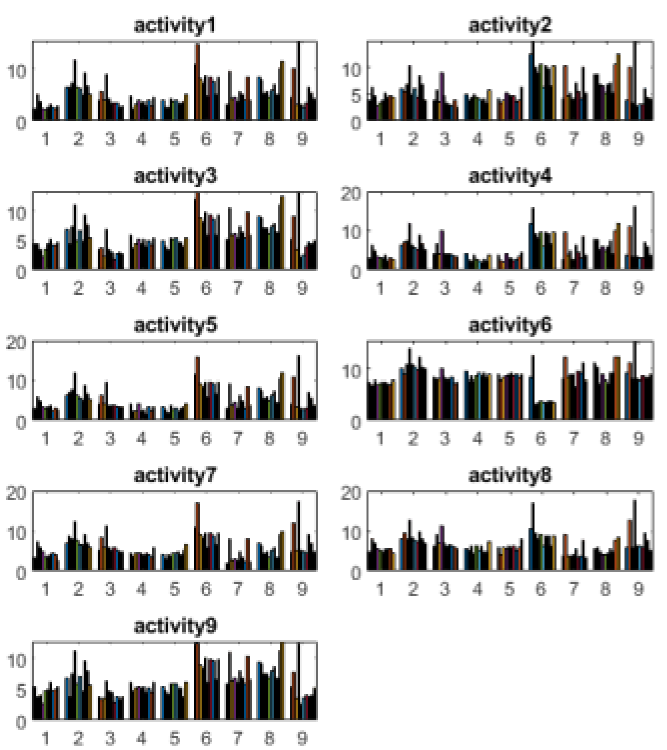

Fig. 3. Euclidean distance d (vertical axis) between mean activity vector and selected activity vector, for 9 activities and 10 participants, grouped by activities (horizontal axis), IMU placed on non-dominant arm, gyroscope

TABLE I
FEATURES EXTRACTED FROM ACCELEROMETER, GYROSCOPE AND MAGNETOMETER SIGNALS FOR EVERY ACTIVITY WITH MATLAB FORMULAS

Feature and Matlab formula
Mean value for each axis (x, y, and z) M = [mean(signal)];
Average Mean over 3 axes AM = mean(M);
Standard Deviation value for each axis (x, y, and z) SD = [std(signal)];
Average Standard Deviation over 3 axes ASD = mean(SD);
Skewness value for each axis (x, y, and z) S = [skewness(signal)];
Average Skewness over 3 axes AS = mean(S);
Kurtosis value for each axis (x, y, and z) K = [kurtosis(signal)];
Average Kurtosis over 3 axes AK = mean(K);
Energy value for each axis (x, y, and z) E = sum((abs(fft(signal))).$^2)/length(signal)$;
Average Energy over 3 axes AE = mean(E);
Correlations C = [corr(signal(:,1), signal(:,2)), corr(signal(:,2), ... signal(:,3)),corr(signal(:,1), signal(:,3))];
Hjorth parameters Activity Act = var(signal);
Mobility Mob = sqrt(var(diff(signal))./var(signal));
Complexity Com = sqrt(var(diff(diff(signal)))./var(signal));
Spectral Purity Index SPI = (var(diff(signal)).$^2)./(var(signal).*var(diff(diff(signal)))$

sensor,for IMU's placed on lower back and hip are presented on Figure 7. Maps of average distances from activity vector are presented on Figure 8. Minimum distances from activity vector (minimum of each row in map of average distances) for maps presented on Figure 8 are presented on Figure 9.

IV. DISCUSSION

We evaluated our experiment to assess the optimal placement of 9-axial inertial measurement unit during observation of children physical activity and to check whether proposed activities can be recognized based on 35 defined parameters. For correctly recognized activities the minimum of average

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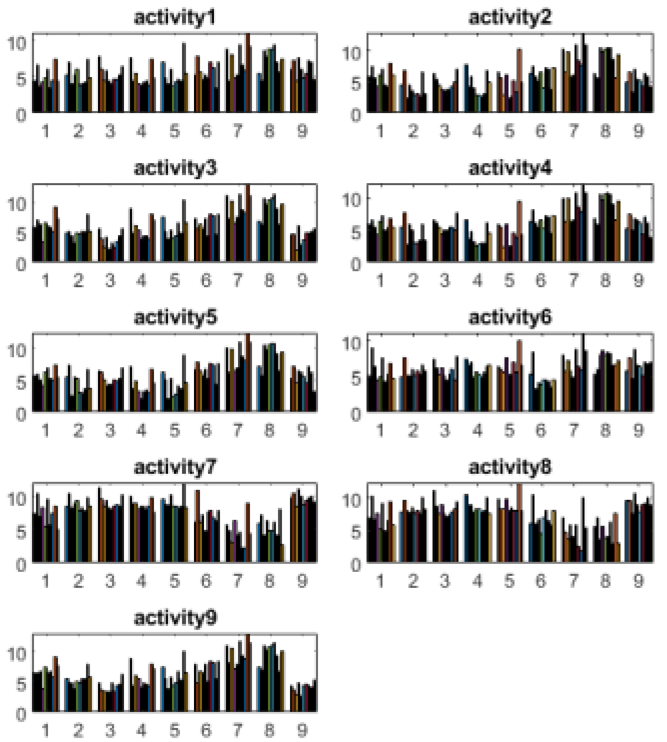

Fig. 4. Euclidean distance d (vertical axis) between mean activity vector and selected activity vector, for 9 activities and 10 participants, grouped by activities (horizontal axis), IMU placed on non-dominant arm, magnetometer

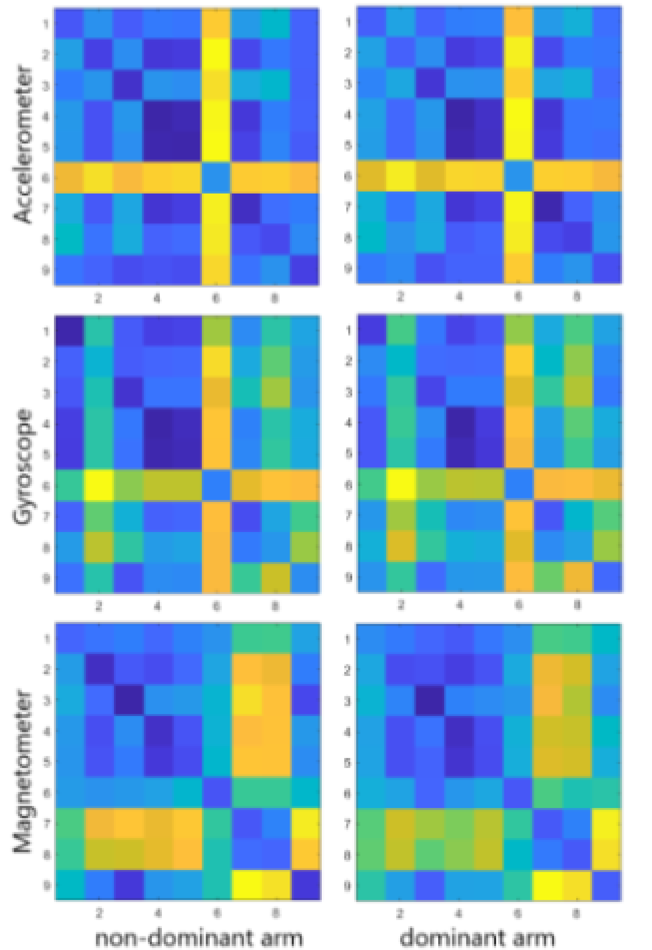

Fig. 5. Maps of average distances from activity vector separately for each sensor, IMU's placed on both arms (dark blue - minimum value, yellow - maximum value)

TABLE II
SENSORS WITH CORRECTLY RECOGNIZED ACTIVITIES
(A-ACCELEROMETER, G-GYROSCOPE, M-MAGNETOMETER)

Activities	n.d. arm	d. arm	lower back	hip
1. jumping	AGM	AG	AGM	GM
2. rotating	M	-	M	M
3. running	AGM	AGM	AGM	AGM
4. walking	AGM	AGM	A	AG
5. walking on tiptoe	A	-	AG	AG
6. clapping hands	AGM	AGM	AM	AG
7. standing still	AGM	AGM	AM	AGM
8. sitting still	AM	AM	AG	-
9. dancing	AM	AG	-	AG

distance from activity vector should be located on the diagonal of average distances map. As it is shown on Figure 6 and Figure 7 the trace of matrices containing locations of minimum distances from activity vector changes with sensor type and placement of IMU. The best result was for accelerometer and magnetometer on non-dominant arm (trace of minimum distances matrix = 8) the worst was for gyroscope - lower back and magnetometer - hip (trace = 4). The mean value of minimum distances matrix trace was 7 for non-dominant arm and 6 for dominant arm. For sensors placed on waist the mean value of minimum distances matrix trace was 5.33 for lower back and 5.67 for hip. For minimum distances maps of activity vectors containing data from three sensors (accelerometer + gyroscope + magnetometer, Figure 9) traces vary from 5 for non-dominant arm and dominant arm to 6 for low back and hip. Table III presents the connection with activities and sensors that gives an information which sensor can be used in given activity recognition. The vast majority of activities were correctly recognized from accelerometers signals. Rotating was correctly recognized only from magnetometer signals. Running was correctly recognized from all the sensors. Walking was better recognized from sensors placed on arms than from that placed on the waist while walking on tiptoe was better recognized from sensors placed on the waist. Clapping hands was recognized both from sensors placed on arms and from that placed on the waist, but the result for hands was slightly better. Standing still was easier to recognize than sitting still. Dancing were not recognized from sensors placed on lower back.

The presented study has a number of limitations. First, the number of subjects is only 10 and end every activity recording lasts only 10 s, so to get more reliable results measurements should be repeated on a bigger group, with activity time prolonged. Second, the small size of our dataset

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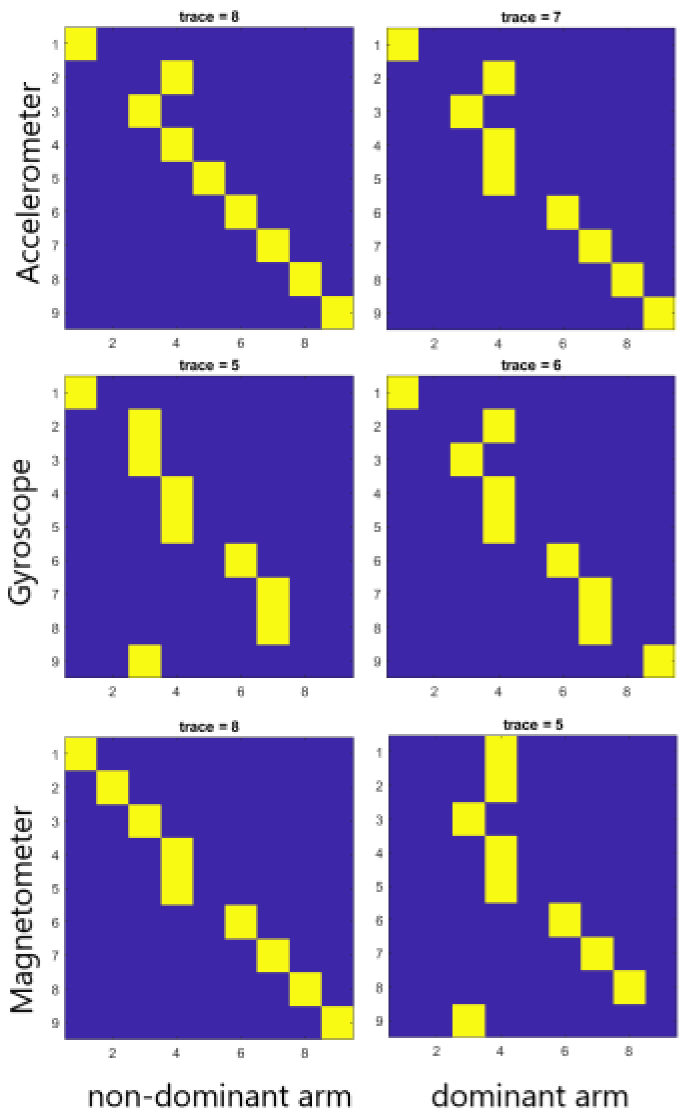

Fig. 6. Minimum distances from activity vector (yellow), separately for each sensor, IMU's placed on both arms (location of minimum of each row in map of average distances)

was the reason behind using only simple classification instead of machine learning algorithms in our activity recognition. Third, some activities, like walking and walking on tiptoe are hardly distinguishable, so additional analysis including re-examination of the selection of appropriate descriptors should be performed.

V. Conclusion

There was no significant difference between results obtained for dominant and non-dominant arm and between lower back and hip-worn sensors, we concluded it from the number of correctly matched activities. As it is showed on Figure 8 and 9 number of correctly matched activities is the same for both sensors, it means that we can choose the configuration that is, in our opinion, more comfortable for children.

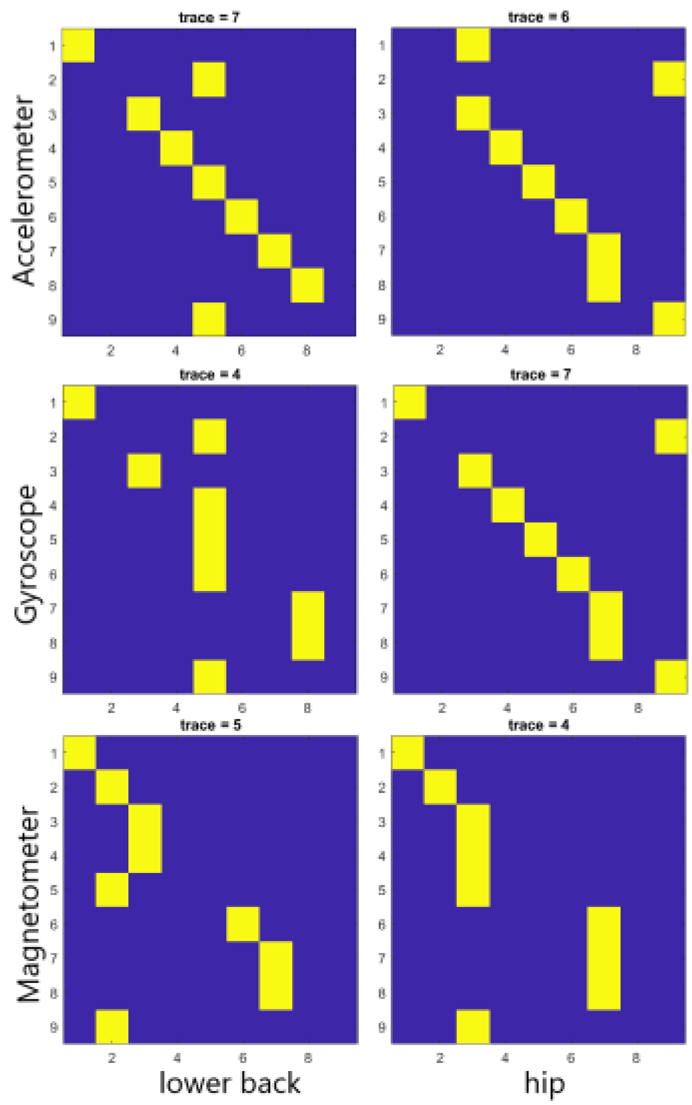

Fig. 7. Minimum distances from activity vector (yellow), separately for each sensor, IMU's placed on lower back and hip (location of minimum of each row in map of average distances)

Our dataset was small, but performed analyzes are a good starting point for further research. The next stage of our work will be enlarging the existing database and the use of neural network algorithms to correctly recognize defined activities.

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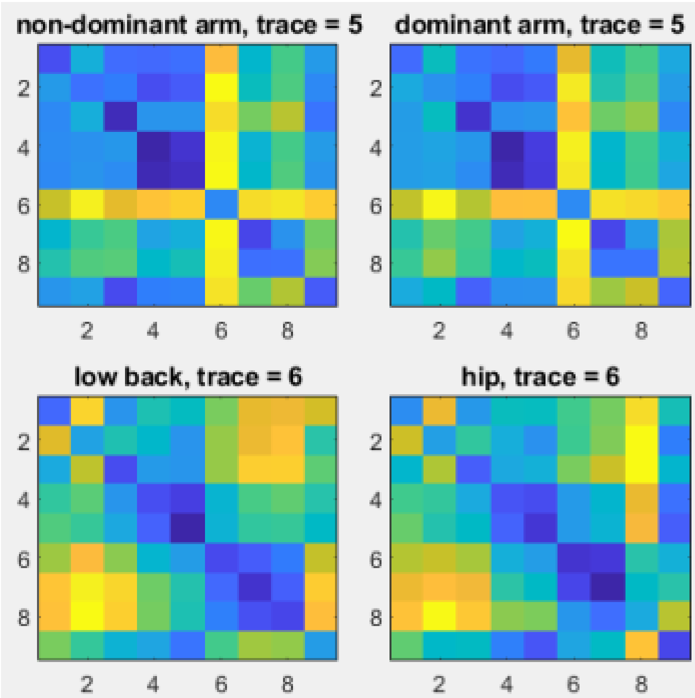

Fig. 8. Maps of average distances from activity vector

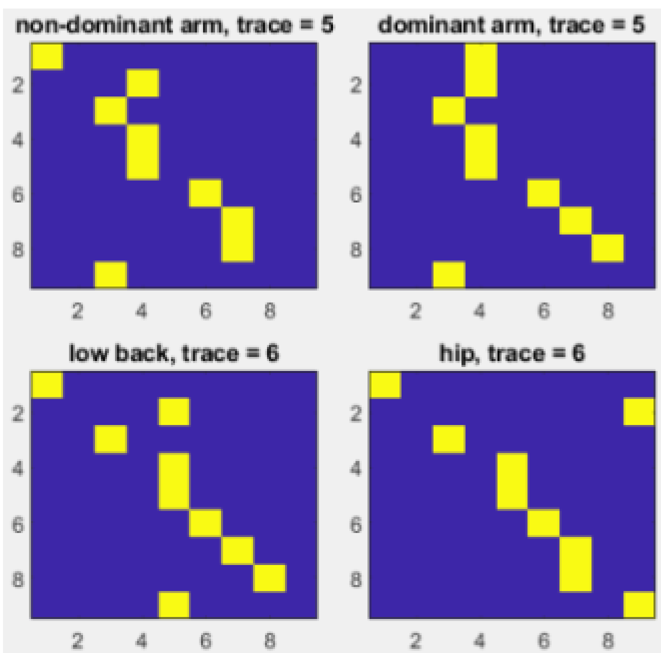

Fig. 9. Minimum distances from activity vector (minimum of each row in map of average distances)

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