Method (experiments) chapter should have all the detail that someone needs to do exactly the same experiment. It should be like a cookery book that gives a recipe for making something. Is everything in this chapter?

Chapter 4

Experiments

4.1 Aims

Not only tackling the weaknesses and robustness of RSS, UTDE, embedding parameters, RP and RQA metrics regarding different conditions for time-series (smoothness, windowsizes and structures), but also considering the models of Stergiou et al. (2006) and (Vaillancourt and Newell, 2002, 2003) for movement movement variability, we design two experiments in the context of human-humanoid interaction where participants perform simple arm movements repetitions.

4.2 Participants

For this thesis, twenty-three participants, from now on defined as pN where N is the number of participant, were invited for two experiments of simple arm movements. Although the same number of participants were invited for the experiments, different number of participants were take into account for each of the experiments.

4.2.1 Human-Image Imitation Activities

4.2.2 Human-Humanoid Imitation Activities

For the experiment of Human-Humanoid Imitation Activities, data for only twenty participants were analysed since the instructions for $p01$, who was the only left-handed, were mistakenly given in a way that movements were performed different from what had been planned, and for participants $p13$ and $p16$ data were corrupted because bluetooth communications problems with the sensors. With that in mind, all of the 20 participants were right-handed healthy participants, being four females and sixteen males, with a mean and standard deviation (SD) age of mean=19.8 (SD=1.39) years.

4.3 Equipment

During the experiments, time series were collected with four neMEMSi Inertial Measurement Units (IMUs) using a sampling rate of 50Hz (Comotti et al., 2014). neMEMSi sensors provide tri-axial time series from the accelerometer, gyroscope and magnetometer sensors and quaternions. A further technical information regarding the NeMEMSi IMU sensors is given in Appendix B.1. For the human-humanoid imitation activities, NAO, a humanoid robot from Aldebaran (Gouaillier et al., 2009), were programmed with choreographer to perform horizontal and vertical arm movements. A further technical information regarding NAO and the code of NAO's movements is given in Appendix B.3

4.4 Ethics

For the experiments of this thesis conducted in November 2016, participants confirmed reading and understanding the participant information sheet for the experiments and were able to withdraw from the experiment at any time without giving any reason. The design of the experiments is adhered to University of Birmingham regulations and data were anonymised and stored only a personal computer in accordance with the Data Protection Act 1998. For further information about the ethics, online participation information sheets and experiment check list, refer to Appendix C.

4.5 Experiments

4.5.1 Human-Image Imitation Activities

For the human-image imitation (HHI) experiment four wearable IMUs sensors were used and attached to the right hand of the participant (Figure 4.1 A,D). Participants performed two experiments: (i) an unconstrained arm movement imitation activity where participants only receive instructions and look an images of the movement and, (ii) a constrained experiment where participants hear a beat to synchronise their arm movements.

Arm movements following an image while not hearing a beat

Participants received instructions to perform upper arm movements while only looking an image of:

- ten repetitions of horizontal arm movement at their comfortable speed (Fig. 4.1(A, B, C)),
- ten repetitions of vertical arm movement at their comfortable speed (Fig. 4.1(D, F, E)),
- ten repetitions of horizontal arm movement at a faster speed than the comfortable speed but not at their fastest speed (Fig. 4.1(A, B, C)), and

- ten repetitions of vertical arm movement at a faster speed than the comfortable speed but not at their fastest speed (Fig. 4.1(D, F, E)).

Arm movements following an image while hearing a beat

Participants received instructions to perform upper arm movements while listening a beat to constraint their movements.

- ten repetitions of horizontal arm movement at normal speed (Fig. 4.1(A, B, C)),
- ten repetitions of vertical arm movement at normal speed (Fig. 4.1(D, F, E)),
- ten repetitions of horizontal arm movement at faster speed and (Fig. 4.1(A, B, C)), and
- ten repetitions of vertical arm movement at faster speed (Fig. 4.1(D, F, E)).

4.5.2 Human-Humanoid Imitation Activities

For the human-humanoid imitation (HHI) experiment four wearable IMUs sensors were used in which two sensors were attached to the right hand of the participant and two sensors were attached to the left hand of the humanoid robot (Figure 4.2 A,C). Then, in the face-to-face imitation activity each participant was asked to imitate repetitions of simple horizontal and vertical arm movements performed by the humanoid robot in the following conditions:

- ten repetitions of horizontal arm movement at normal (HN) and faster (HF) speed (Fi. 4.2 A), and
- ten repetitions of vertical arm movement at normal (VN) and faster (VF) speed (Fig. 4.2 C).

The normal and faster speed of arm movements is defined by the duration in number of samples of one repetition of NAO's arm movements. We select NAO's arm movements duration to distinguish between normal and faster arm movements as the movements

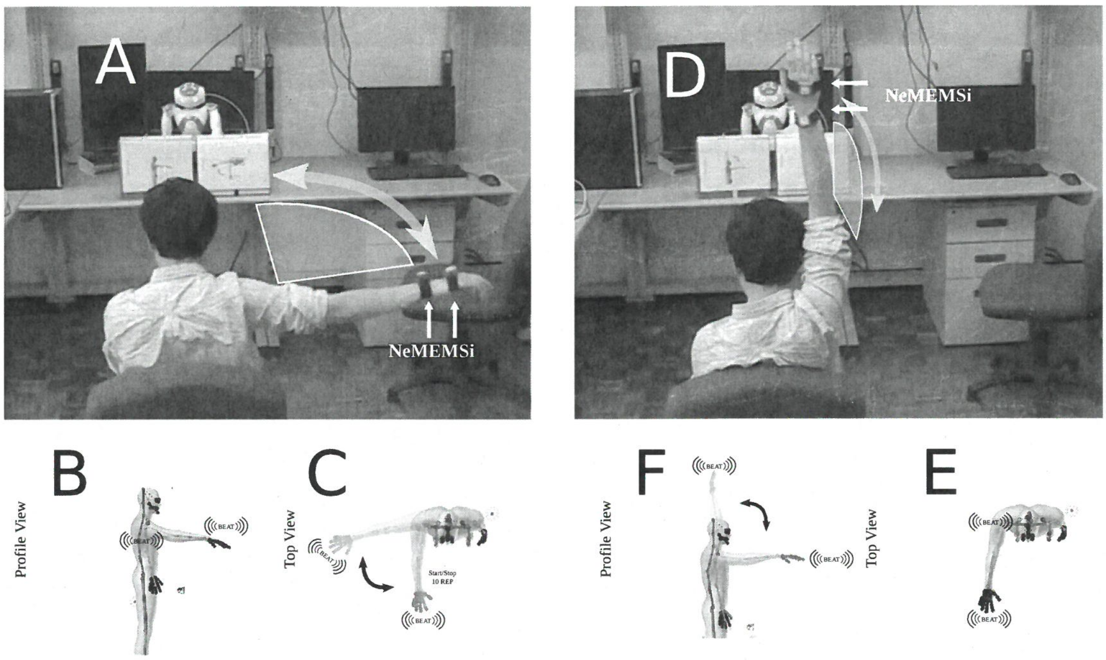

Fig. 4.1 **Human-image imitation (HII) activities.** (A) HII of horizontal arm movement, (B) image of the profile view for horizontal arm movement, (C) image of the top view for horizontal arm movement, (D) HII of vertical arm movement, (E) image of the profile view for vertical arm movement, and (F) image of the top view for horizontal arm movement. (B, C, F and E) show '(((BEAT)))' to indicate the participants arm movements synchronisation when hearing a beat.

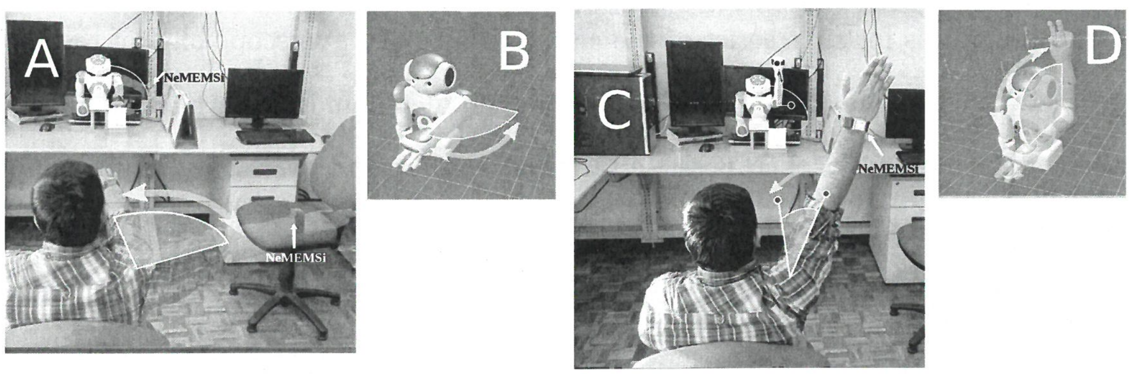

Fig. 4.2 **Human-humanoid imitation activities.** Face-to-face human-humanoid imitation (HHI) activities for (A) HHI of horizontal arm movement, (B) Humanoid horizontal arm movement, (C) HHI of vertical arm movement, and (D) Humanoid vertical arm movement.

from the humanoid robot have less variation between repetition to repetition. The duration for one repetition of the horizontal arm movement at normal speed, HN, is about 5 seconds considering that each repetition last around 250 samples. For horizontal arm movement at faster speed, HF, each repetition were performed in around 2 seconds which correspond to 90 samples of data. The vertical arm movement at normal speed, VN, were performed in 6 seconds which is around 300 samples of data. For vertical arm movement at faster speed, VF, each repetition lasts about 2.4 seconds which correspond to 120 samples of data. To visualise the distinction between normal and faster speed for horizontal and vertical arm movements, Fig 4.3 shows smoothed time series for axes Z and Y of the gyroscope sensors with four window lengths: 2-sec (100-samples), 5-sec (250-samples), 10-sec (500-samples) and 15-sec (750-samples).

4.6 Preparation of time series

4.6.1 Raw time-series

Considering the work of Shoaib et al. (2016) which provided evidence of an improvement in recognition activities when combining data from accelerometer and gyroscope, ~~We focus our~~ analysis for time series uses only ~~of~~ the accelerometer and gyroscope ~~uses~~ ~~only~~ of the IMU sensors~~, and~~ which leaves the ~~time series of the~~ magnetometer and quaternions for future investigations because of their possible variations with regard to magnetic disturbances.

Time series from the accelerometer are defined by triaxial time series $A_x(n)$, $A_y(n)$, $A_z(n)$ which forms the matrix $\boldsymbol{A}$ (Eq. 4.1), and the same for data from the gyroscope which is defined by triaxial time-series of $G_x(n)$, $G_y(n)$, $G_z(n)$ representing the matrix $\boldsymbol{G}$ (Eq. 4.2). Both triaxial time series of each sensor, a and g, are denoted with its respective axes subscripts x, y, z, where n is the sample index and N is the same maximum length of all axes for the time series. Matrices $\boldsymbol{A}$ and $\boldsymbol{G}$ are represented as

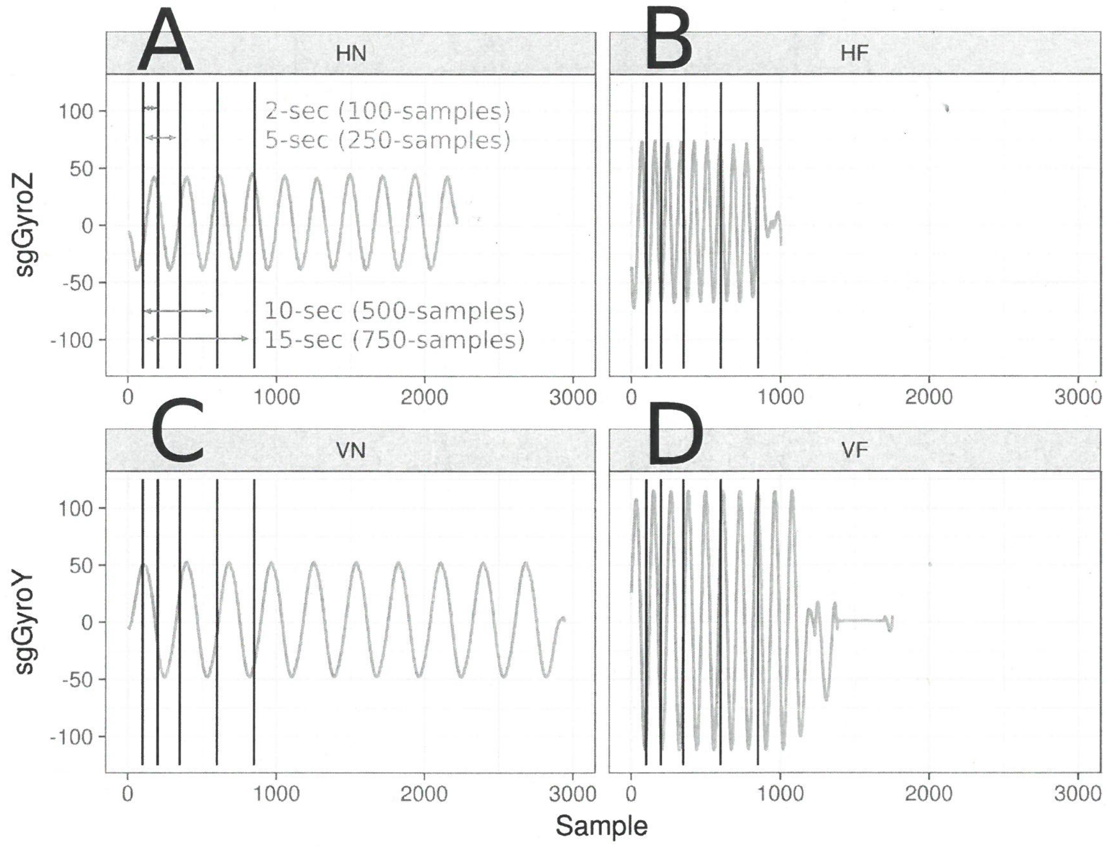

Fig. 4.3 **Time series duration of horizontal and vertical arm movements.** Time series of smoothed data from gyroscope sensor for different speed arm movements performed by NAO: (A) Horizontal Normal arm movement, HN, (B) Horizontal Faster arm movement, HF, (C) Vertical Normal arm movement, VN, and (D) Vertical Faster arm movement, VF. Additionally, (A) shows window sizes for 2-seconds (100 samples), 5-seconds (250 samples), 10-seconds (500 samples) and 15-seconds (750 samples) which are also presented in (B), (C) and (D). R code to reproduce the figure is available Xochicale (2018).

follows:

$$\boldsymbol{A} = \begin{pmatrix} A_x(n) \\ A_y(n) \\ A_z(n) \end{pmatrix} = \begin{pmatrix} a_x(1), a_x(2), \ldots, a_x(N) \\ a_y(1), a_y(2), \ldots, a_y(N) \\ a_z(1), a_z(2), \ldots, a_z(N) \end{pmatrix}, \tag{4.1}$$

$$\boldsymbol{G} = \begin{pmatrix} G_x(n) \\ G_y(n) \\ G_z(n) \end{pmatrix} = \begin{pmatrix} g_x(1), g_x(2), \ldots, g_x(N) \\ g_y(1), g_y(2), \ldots, g_y(N) \\ g_z(1), g_z(2), \ldots, g_z(N) \end{pmatrix}, \tag{4.2}$$

where n is the sample index and N is the same maximum length of all axes for the time series.

4.6.2 Postprocessing time-series

After the collection of raw time-series from four NeMEMsi sensors, time synchronisation alignment and interpolation were performed in order to create time series with the same length and synchronised time. We refer the reader to Appendix B for technical information about the time synchronisation process and IMU sensors.

4.6.3 Normalization of time-series

Tim series are normalised to have zero mean and unit variance using sample mean and sample standard deviation (Ioffe and Szegedy, 2015). The sample mean and sample standard deviation using $x(n)$ is given by

$$\mu_{x(n)} = \frac{1}{N}(\sum_{i=1}^{N} x(i)), \quad \sigma_{x(n)} = \sqrt{\frac{\sum_{1=1}^{N}(x(i) - \mu_{x(n)})^2}{N-1}}, \tag{4.3}$$

then the normalised data, $\hat{x}(n)$, is computed as follows

$$\hat{x}(n) = \frac{x(n) - \mu_{x(n)}}{\sigma_{x(n)}}. \tag{4.4}$$

4.6.4 Smoothing time-series

Using a low-pass filter is the common way to either capture the low frequencies that represent %99 of the human body energy or to get the gravitational and body motion

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is this a real statistic?

components of accelerations (Anguita et al., 2013). However, for this thesis the main focus in on the conservation of the structure of the time series in terms of the width and heights where, for instance, a Savitzky-Golay filter can help to accomplish such task (Press et al., 1992). Savitzky-Golay filter is based on the principle of moving window average which preserves the area under the curve (the zeroth moment) and its mean position in time (the first moment) but the line width (the second moment) is violated and that results, for example, in the case of spectrometric data where a narrow spectral line is presented with reduced height and width. The aim of Savitzky-Golay filtering is to find the filter coefficients c_n that preserve higher momentums which are based on local least-square polynomial approximations (Press et al., 1992; Savitzky and Golay, 1964; Schafer, 2011). Hence, Savitzky-Golay coefficients are ~~therefore~~ computed using an R function `sgolay(p,n,m)` where `p` is the filter order, `n` is the filter length (must be odd) and `m` is the m-th derivative of the filter coefficients (signal R developers, 2014). Smoothed signal is represented with a tilde over the original signal: $\tilde{x}(n)$.

4.6.5 Window size of time-series

With regard to the window size, Shoaib et al. (2016) compared ~~investigated its effects using~~ seven window lengths (2, 5, 10, 15, 20, 25, 30 seconds) and combination of inertial sensors (accelerometer, gyroscope and linear acceleration sensor) in activity recognition performance for repetitive activities (walking, jogging and biking) and less repetitive activities (smoking, eating, giving a talk or drinking a coffee). Similarly, Shoaib et al. (2016) experimented with different window size effect to conclude that the increase of window size improved the recognition of complex activities because these required a large window to learn the repetitive motion patterns. Also, Shoaib et al. (2016) concluded that the use of large window size improve the recognition performance of less repetitive activities which mainly involve random hand gestures.

For the activities in this thesis which are mainly repetitive, we selected only four window sizes: 2-s window (100 samples), 5-s window (250 samples), 10-s (500 samples) and 15-s window (750 samples) (Figure 4.3).