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SWIMMING LIKE OSCILLATORS ? THE QUESTION OF MODELLING AND IDENTIFYING PARAMETERS

R. Charrier, N. Corson, L. Seifert, J. Komar, C. Bertelle *†‡

Abstract. This paper addresses the knee and elbow evolution during a swimming cycle. From data collected in a sport lab, the aim is to construct an oscillator model and to identify parameters in order to exhibit the same dynamical behaviour. Literature gives an idea of oscillators which can be used to start with. Indeed, in other sports, Van der Pol and Rayleigh nonlinear dynamical systems have already been used to model athletic movements. Starting from this point, we have applied a PSO-like algorithm to fit parameters with a hybrid theoretical model of Rayleigh-Van der Pol. Results are convincing for a restricted set of original data, showing that the chosen theoretical model has to be enhanced.

Keywords. Nonlinear oscillators, Parameter identification, Data, Dynamical systems,.

1 Introduction

Mathematical and Computer science models can contribute to the search of performance and training of high level athletes. Beyond new technologies we can use, especially in terms of sensors and images analysis, it remains very important to understand and analyse the movement coordination according to the environment (air, water), taking into account the movement complexity. This coordination can be either intuitive or controlled.

Learning methods to tend to expert movements remains open problems in research. Indeed, physical, behavioral and psychological elements have to be taken into account.

The first part of this paper consists in constructing models, using oscillators, of knee and elbow behaviors through a breaststroke cycle, based on data obtained from real swimmers wearing sensors.

The second part of this paper addresses the design and the use of an algorithm to identify parameters according to the level of the swimmer.

For example, in other sports such as ski, it has been shown through the study of Hooke portraits, giving the acceleration according to the speed, that an expert behavior

was quite well represented with a Van der Pol oscillator whereas a beginner behavior could be quite well represented with a Rayleigh oscillator [Teulier et al., 2006, Nourrit et al., 2003]. The aquatic environment of swimmer may change this observation in the swimming case.

2 Model design and Parameter identification

2.1 Collecting data

Breaststroke: In breaststroke swimming, achieving high performance requires a particular management of both arm and leg movements, in order to maximise propulsion and optimise the glide and recovery times. Therefore, expertise in breaststroke is defined by adopting a precise coordination pattern between arms and legs (i.e. a specific spatial and temporal relationship between elbow and knee oscillations). Indeed, when knees are flexing, elbows should be fully extended (180°), whereas knees should be fully extended (180°) when elbows are flexing, in order to ensure a hydrodynamic position of the non-propulsive limbs when the first pair of limbs is actually propulsive.

Data: Participant performed 10 trials of 25-m swim during each session, with 1 x 25-m consisting approximately in 8 recorded cycles (one cycle correspond to the period between two successive maximal knee flexion). Coordination between elbow and knee was defined by the continuous relative phase between these two oscillators, considering elbows and knees as acting like individual pendulums. A value of relative phase close to -180° or 180° defined an anti-phase relationship (i.e. opposite movements of knee and elbow) while a value close to 0° defined an in-phase mode of coordination (i.e. identical movements of knee and elbow). Each cycle performed during the learning process was therefore defined by a time series of continuous relative phase (normalised to 100 values) describing the relationship between the knee and the elbow during all the swimming cycle.

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Sensors: During every learning session, all learners were equipped with small motion sensors on both arms and legs including a data logger and recording elbow and knee angle at a frequency of 200 Hz. Four small inertial centrals were fixed on the right leg and right thigh to record knee angle and on the right forearm and right arm to assess the elbow angle. These sensors combines 3D gyroscope (1600°/s), 3D accelerometer (+/-8G) and 3D magnetometer (MotionLog, Movea©, Grenoble, France). These sensors used North magnetic and gravity references. The advantage of using sensor is that all the cycles performed by each swimmer were recorded during the entire learning process and available for the analysis (i.e. 8 cycles x 10 trials x 16 sessions = approximately 1280 cycles per learners).

2.2 Plotting data

In this section, we analyse experimental data collected during beginner sessions. Thanks to litterature, we have the idea that a hybrid Van der Pol - Rayleigh oscillator model could fit data.

Experimental data are given as time series of knee and elbow angle. The sampling frequency is $f = 200Hz$.

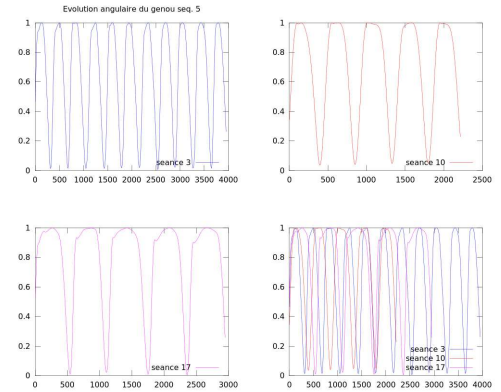
In the case of the elbow, data of three swimming sessions are used : 3, 10 et 17. Each session is itself divided into ten swimming sequences. The speed and acceleration are computed using a polynomial interpolation. This method prevents us from numerous computation artefacts because of the noise in data. To go through these drawbacks, we interpolate a sample of 50 points before and after the current point with a polynom of a sufficiently high degree (degree 10 in our case) so that we can compute proper derivatives on each point.

This way, we can obtain phase portraits and hooke portraits from the time series. Figure 1(a) shows the knee datas for three sessions. Figure 1(b) shows the phase portraits (angular speed according to angle), and figure 1(c) shows Hooke portraits, meaning the angular acceleration according to the angle.

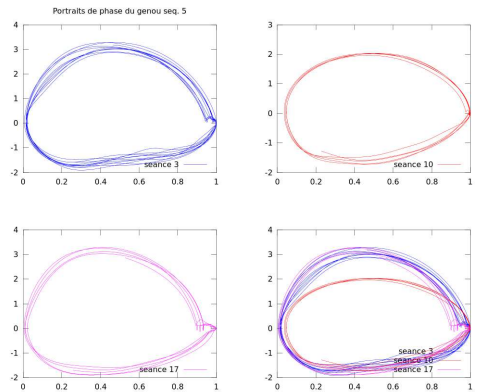
This first visualisation allows to have an idea of the model which could be used to obtain the same behavior. Indeed, we can see that during sessions 3 and 17, cycles of the attractor (cf. figure 1(b)) are not symmetric and that the speed remains zero for a while (cf. time series). This introduces a delay in the data cycles. This asymmetric behavior will make the parameter identification of the Van der Pol - Rayleigh model much more complicated. This is why, as a first step, we will focus on session 10.

2.3 Hybrid Rayleigh - Van der Pol model

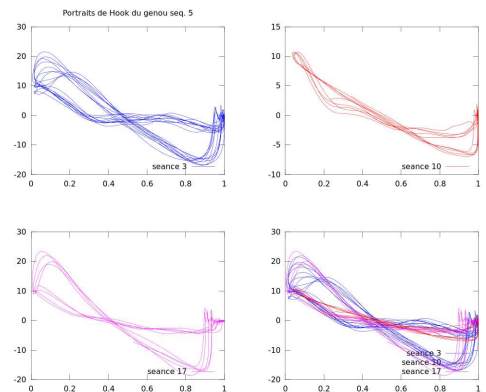
In this field of research, periodic behavior of human movements are often studied using Van der Pol or Rayleigh oscillatoors [Beek et al., 1995, Beek et al., 2002, Delignières et al., 1999]. This model is described by the



(a) Angle time series



(b) Phase portraits



(c) Hook Portraits

Figure 1: Normalized data of knees and elbows during the same cycle of a swimming cycle.

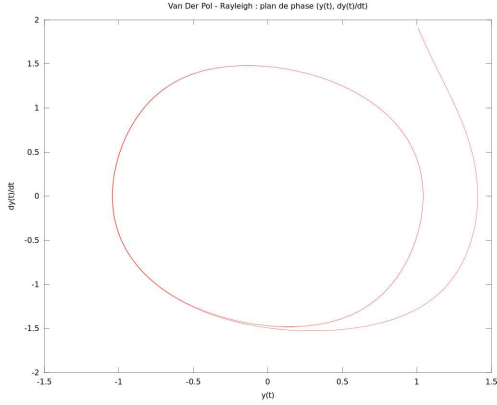


Figure 2: Phase portrait of a hybrid Rayleigh - Van der Pol model, with : $t_0, \gamma = 2.0, \epsilon = 1.2, \delta = 1.0, \omega = 1.5$

following differential equations :

$$\ddot{x} - (\gamma - \epsilon x^2 - \delta \dot{x}^2)\dot{x} + \omega^2 x = 0 \quad (1)$$

where $x(t)$ is the variable, \dot{x} et \ddot{x} are its two first time derivatives [Huys and Jirsa, 2011]. All parameters are positive, and this model can be rewritten as a two dimensional differential system as follows:

$$\begin{cases} \dot{x} = y \\ \dot{y} = (\gamma - \epsilon x^2 - \delta y^2) y - \omega^2 x \end{cases} \quad (2)$$

The trajectories of such a differential system can be visualized for example on figure 2.

We aim at identifying as well as possible (i.e. in the mean of least squares) solutions of this differential model to experimental data.

Let $\tilde{x}(t)$ the time series corresponding to experimental data. This problem consists of finding the parameter set $(\gamma, \epsilon, \delta, \omega)$ which minimize the following objective function:

$$F = \frac{1}{N} \sum_{i=0}^{N-1} (x(t_i) - \tilde{x}(t_i))^2 \quad (3)$$

N is the number of considered sampling.

The following section presents an algorithm to realize this optimization.

2.4 Chaotic PSO for parameter identification

This optimization problem is a difficult one since it is a nonlinear, continuous variable identification problem. The parameter space is large enough so that classical methods such as Levensberg-Marquardt cannot be used [Ljung, 2010].

In this case, alternatives are said “soft computing” approaches using metaheuristics for optimization. One of

these metaheuristics is inspired by the collective behavior of social insects. This gives rise to optimization algorithms by swarms of particles in which every possible solution is represented by a particle moving in the search space for finding the best position. On each explored point, the particle computes the objective function and shares this information with the rest of the swarm. This method can be summarized by the following dynamical system, governing particle i :

$$\begin{cases} \mathbf{v}_i(t+1) = w \mathbf{v}_i(t) + c_1(\mathbf{x}_b(i) - \mathbf{x}_i(t)) \\ \quad + c_2(\mathbf{x}_g - \mathbf{x}_i(t)) \\ \mathbf{x}_i(t+1) = \mathbf{x}_i(t) + \mathbf{v}_i(t+1) \end{cases} \quad (4)$$

where $\mathbf{x}_b(i)$ and \mathbf{x}_g are respectively the best position of the current particle through its own history and the best position within the group at time t only. Parameters w, c_1 and c_2 are random coefficients in a certain range, representing respectively an inertia coefficient (controlling the importance of the exploration phase in the search space) and two coefficients of balance between individual and collective performance.

For this study, we used this kind of algorithm adding a local search from the best position of the group at time t using chaotic maps for exploration. It appears that these applications are more powerful than a classical random uniform creation of parameter sets. This is due to their very specific probability density giving advantage to extrem and central values of the search range [Yang et al., 2012]. The chaotic map used for the local research is the following:

$$x_{n+1} = \frac{\sin(4\pi x_n) + 1}{2}$$

This kind of algorithm, named Chaotic PSO in many papers, is used since about ten years. Results presented in the next section are obtained with this method.

3 Results

Results presented here concern training sessions named $E3, E10, E17$. Sessions 3 and 10 are the better ones in term of parameter identification, in particular concerning the elbow angle (cf. fig. 3 and 4). Other series have been studied but less successfully (cf. fig. 5 et 6).

We can observe a real variability of exploration according to the best performance. The best fitness function gives from 0.2% to 0.5% average quadratic error and the obtained attractors follow the experimental trajectories for sessions $E3$ and $E10$ of the elbow, despite the noise of measure. Differential equations corresponding to identifications are given in table 4. We can then follow the evolution of the parameter values to see if a behavior corresponds whether to a Rayleigh or a Van der Pol one, looking at two specific parameters.

3.1 Discussion

Results of identification allow to conclude that, unlike the skiing case, a swimmer behavior can rarely be assimilated to a Rayleigh-Van der Pol oscillator. Indeed, identification fits quite well in the case of sessions 3 and 10 for the elbow. In these cases, it could be very interesting to study the evolution of the parameter values to check if they are significant in terms of learning.

However, the hypothesis of a Rayleigh - Van der Pol dynamic concerning the knee is almost never verified using this identification method. This might be due to the kind of landing on the time series, also observed on the phase portraits (see the right part of the phase portraits of figure 1).

4 Conclusion

Hypothesis on the hybrid de Van der Pol-Rayleigh model are validated on most of the experimental data in the case of elbow angles. The interest of using this model is that it requires a low number of parameters and allows a simplified representation of the trajectories in the parameter space. However, this model does not fit in most of the knee data.

Acknowledgements

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Appendix A Visualization of identification results

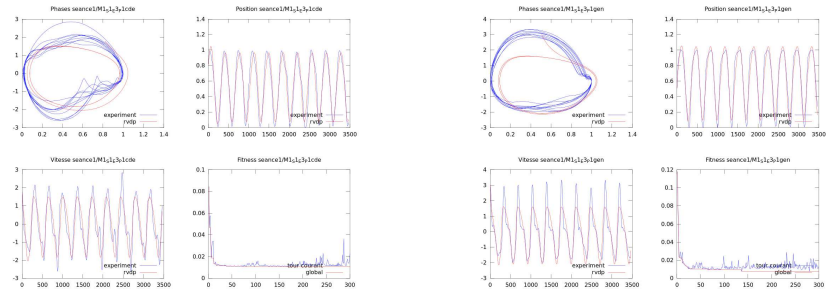
The following results have been obtained using Octave (clone lib of Matlab) with a unique execution, with 100 particles, on 300 principal research loops and 50 local research loops.

Appendix B Model identification

The parameters given in this table are those in the equation (1). They correspond to the best approximation obtained with the chaotic swarm particle algorithm. Let us mention that these simulations have been performed only once.

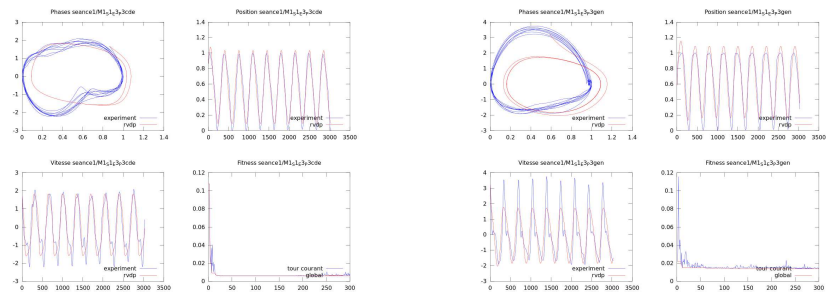
series	γ	ϵ	δ	ω
E3 P1 elbow	3.70	5.95	1.36	4.07
E3 P3 elbow	8.45	10.00	3.52	4.39
E3 P5 elbow	6.93	8.05	3.10	4.05
E3 P7 elbow	6.01	5.10	2.47	4.28
E3 P9 elbow	1.87	9.94	0.51	3.88
E10 P1 elbow	8.65	3.25	3.62	4.50
E10 P3 elbow	5.25	7.46	1.89	3.91
E10 P5 elbow	5.53	9.65	2.42	3.66
E10 P7 elbow	4.22	0.04	1.85	3.61
E10 P9 elbow	4.00	6.17	1.19	3.63
E17 P1 elbow	3.53	8.07	9.86	2.29
E17 P3 elbow	3.20	9.15	9.58	2.44
E17 P5 elbow	1.31	0.03	7.12	2.24
E17 P7 elbow	4.67	8.99	9.72	2.96
E17 P9 elbow	3.51	9.55	9.97	2.76
E3 P1 knee	4.62	4.69	1.11	4.41
E3 P3 knee	2.27	0.15	0.82	3.99
E3 P5 knee	6.96	4.34	3.22	4.06
E3 P7 knee	9.17	3.43	4.44	4.61
E3 P9 knee	8.95	8.64	3.41	4.58
E10 P1 knee	3.39	2.88	0.65	3.62
E10 P3 knee	4.48	0.69	0.76	3.88
E10 P5 knee	3.58	1.29	0.92	3.53
E10 P7 knee	3.30	1.09	1.22	3.49
E10 P9 knee	2.58	0.29	1.30	3.38
E17 P1 knee	4.40	1.74	3.19	2.96
E17 P3 knee	5.61	1.99	3.25	3.37
E17 P5 knee	6.30	3.77	3.83	3.48
E17 P7 knee	9.56	0.00	4.57	4.45
E17 P9 knee	9.86	3.15	6.50	4.55

Swimming like oscillators ?



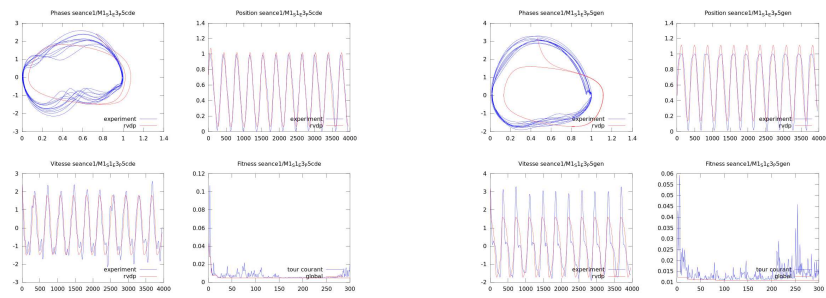
(a) E3 P1 coude

(b) E3 P1 genou



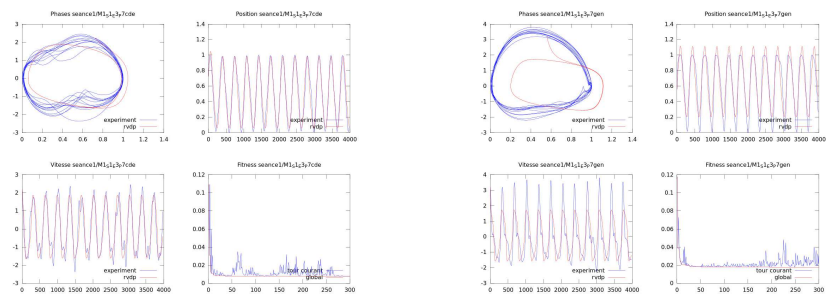
(c) E3 P3 coude

(d) E3 P3 genou



(e) E3 P5 coude

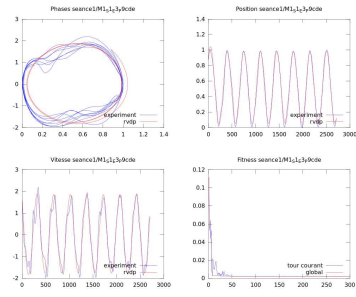
(f) E3 P5 genou



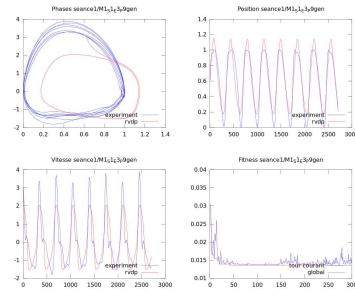
(g) E3 P7 coude

(h) E3 P7 genou

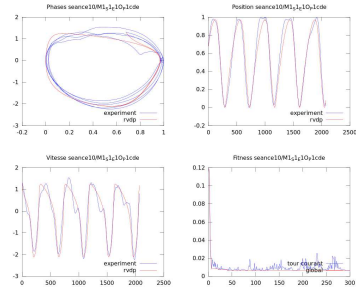
Figure 3: Identification Results using chaotic PSO involving 100 particles after 300 iterations.



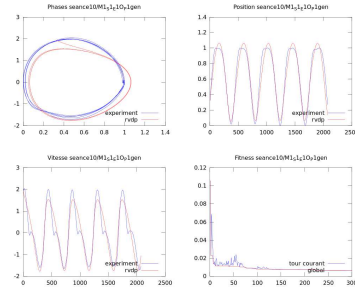
(a) E3 P9 coude



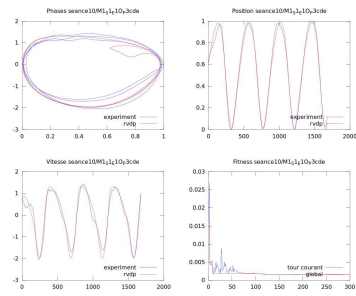
(b) E3 P9 genou



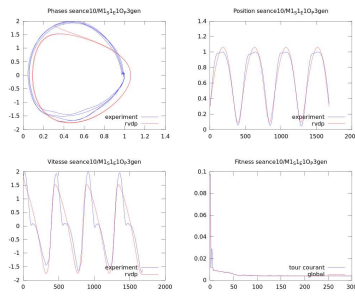
(c) E10 P1 coude



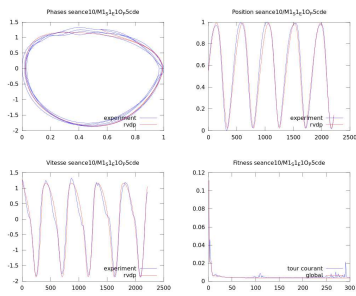
(d) E10 P1 genou



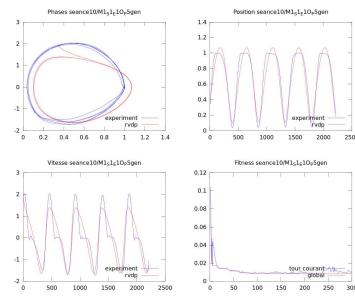
(e) E10 P3 coude



(f) E10 P3 genou



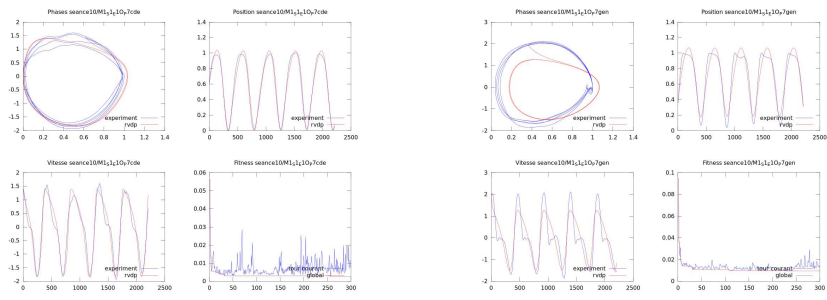
(g) E10 P5 coude



(h) E10 P5 genou

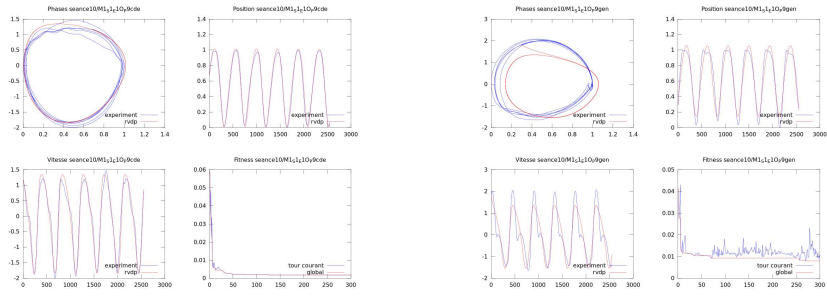
Figure 4: Identification Results using chaotic PSO involving 100 particles after 300 iterations.

Swimming like oscillators ?



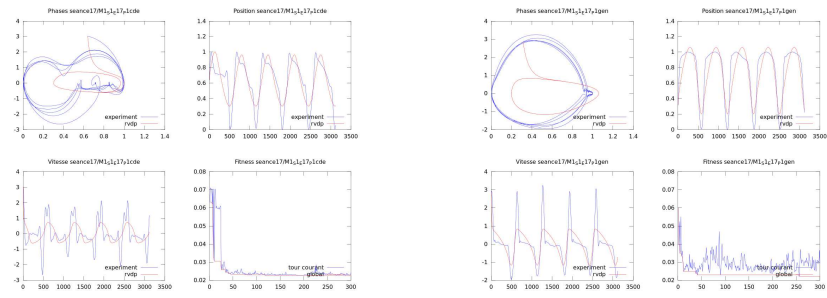
(a) E10 P7 coude

(b) E10 P7 genou



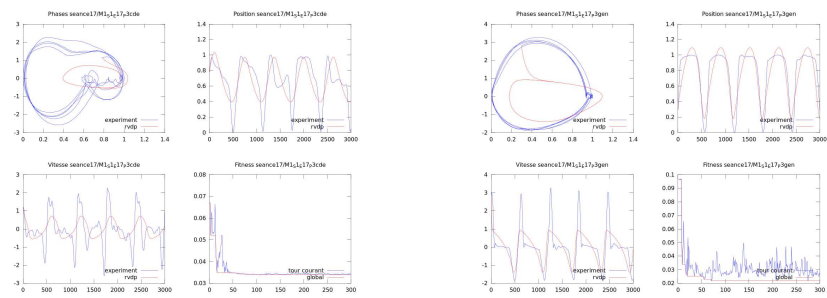
(c) E10 P9 coude

(d) E10 P9 genou



(e) E17 P1 coude

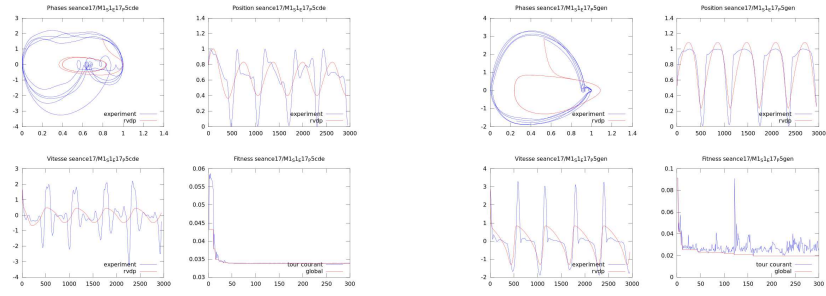
(f) E17 P1 genou



(g) E17 P3 coude

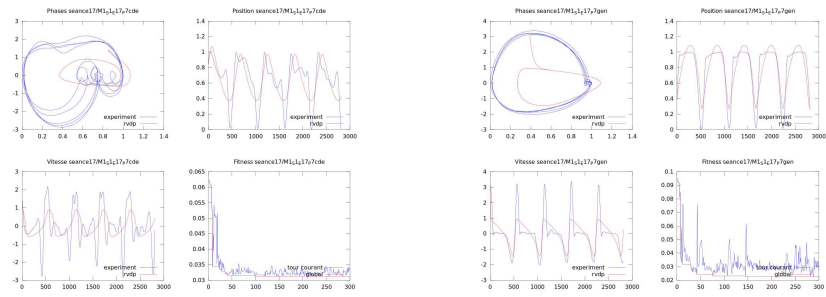
(h) E17 P3 genou

Figure 5: Identification Results using chaotic PSO involving 100 particles after 300 iterations.



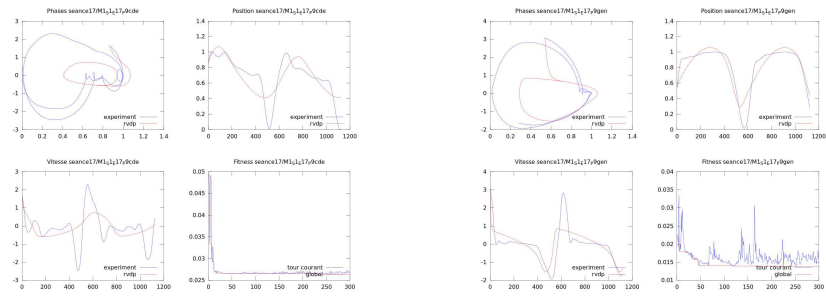
(a) E17 P5 coude

(b) E17 P5 genou



(c) E17 P7 coude

(d) E17 P7 genou



(e) E17 P9 coude

(f) E17 P9 genou

Figure 6: Identification Results using chaotic PSO involving 100 particles after 300 iterations.