HIDDEN MARKOV MODELS APPLIED ONTO GAIT CLASSIFICATION

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ABSTRACT

This paper is about recognition of different gait conditions from body-worn sensor data. Our sensor, located at subject's shank, is a combination of a 3-D accelerometer and a 3-D magnetometer. Stride detection method relies on the use of the sole magnetometer readings. Feature extraction combines both modalities in an original manner and spatial, temporal, and angular parameters are extracted for subsequent classification. Hidden Markov models are employed to identify the types of gait being performed. Different feature modelizations are typically considered with the use of Gaussian mixture laws. This paper analyses which stride feature sets are the most significant and what could be the minimal number of training sequences for best classification scores. Classification performances above 90% are demonstrated.

1. INTRODUCTION

Inertial MEMs-based technology is well suited for *long-term ambulatory monitoring* of physical activity [5]. Indeed accelerometers and gyroscopes are highly-integrated chips that can be embedded into low-power body-worn sensor nodes with on-board memory capability. Several biomedical applications have been designed with this unique capability of remote (from the hospital) monitoring of physical activity [6]. In this framework, *unsupervised gait analysis* is particularly valuable since gait is a good indicator of health status. Several articles have been published on the topic of gait classification from video cameras or from body-worn sensors, where gait features are either based on temporal, spatial or angular gait parameters [1], [3], [7].

The motivation of this work is the assessment of gait activity in hemiplegic patients during ecological conditions. In this context, walking activity will be primarily evaluated using step counting but it is also required to have a better understanding of the type of walking that is being performed. The ultimate goal of the project is to quantify the benefits of rehabilitation therapy for these subjects.

The main contributions of this paper are two-fold with the *gait analysis* being performed with a rather uncommon type of sensor in this context: 3-D accelerometer+3-D magnetometer and a robust hidden Markov model gait classification. Indeed, using anisotropic magnetoresistive sensors, it is possible to sense the relative orientation of the sensor in the surrounding Earth's magnetic field (MF) and resolve the MF in the sensor (or body) frame. The sensor is located at the patient's shank, although other locations may be envisaged (See Fig.1). The proposed approach is carried out in two distinct steps with first the *identification* of stride events along with their characterization [10] and second the stride classification, i.e. the determination of the associated gait class using hidden Markov models [8].

2. STRIDE DELINEATION AND FEATURE EXTRACTION

2.1 Stride detection

The gait cycle in human locomotion is divided into two essential phases with a stance and a swing phase in the approximate 60%-40% ratio [9]. In the sequel, each stride will be time delineated between two successive heel impacts of the same equipped leg.

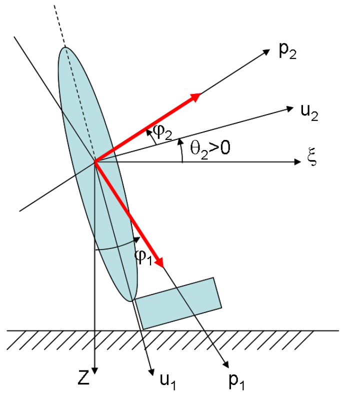

Figure 1: Frame Definition during gait in sagittal plane

As shown in Fig.1, denote (u_1,u_2) the body frame with u_1 the axis along the cranio-caudal direction and u_2 along the antero-posterior direction. Let (Z,ξ) be the inertial frame with Z the axis along the (inertial) vertical direction and ξ along the gait direction. Finally, denote by p_1 the unit vector that supports the projected MF vector in the sagittal plane, from which we build the orthonormal (p_1,p_2) frame.

The proposed stride detection is based on the processing of *shank sagittal magnetometer readings*. The Earth's MF vector, projected in the sagittal plane, is expressed in the inertial (Z-ξ) frame with components :

$$\begin{pmatrix} h_Z \\ h_\xi \end{pmatrix} = \begin{pmatrix} \sin\kappa \\ \cos\theta_1 \cos\kappa \end{pmatrix} = \rho_1 \begin{pmatrix} \cos\varphi_1 \\ \sin\varphi_1 \end{pmatrix} \quad (1)$$

where κ represents the MF dip angle ($\sim 60^\circ$ in France).
We now assume that the (u_1,u_2) frame is simply rotated by the angle θ_2 with respect to the (Z,ξ) frame. Let denote h_{u_1} and h_{u_2} the Earth's MF components resolved in body frame (u_1,u_2), it holds :

$$\begin{pmatrix} h_{u_1} \\ h_{u_2} \end{pmatrix} = \begin{pmatrix} \cos\theta_2 & \sin\theta_2 \\ -\sin\theta_2 & \cos\theta_2 \end{pmatrix} \begin{pmatrix} h_Z \\ h_\xi \end{pmatrix} = \rho_1 \begin{pmatrix} \cos(\varphi_1-\theta_2) \\ \sin(\varphi_1-\theta_2) \end{pmatrix} \quad (2)$$

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By differentiating the phase angle $\varphi_2 = (\varphi_1 - \theta_2)$, it is thus possible to obtain a pseudo shank angular velocity from magnetometer readings. As shown in Fig.2, large angular velocity peaks are particularly visible in the derived signal $\dot{\varphi}_2(t)$ and do correspond to mid-swing (MSW) events during gait [1]. These events can easily be detected using threshold-crossing methods and they serve as robust step identifiers. Furthermore, as already observed in [1] on gyroscope signals, local minima respectively before and after mid-swing event can be identified as toe-off (TO) and heel-strike (HS) events [9]. The whole procedure is now detailed in Algorithm 1.

Algorithm 1 Gait event detection

Input: (h_{u_1}, h_{u_2}) Earth's MF components in body frame,
Input: th_ω Angular velocity threshold (rad/s)
Output: TO_n, MSW_n, HS_{n+1} Gait event ticks.

1. Low-pass filter magnetometer components : $(h_{u_1}, h_{u_2}) \to \left(\widetilde{h}_{u_1}, \widetilde{h}_{u_2}\right)$
2. Cartesian to polar decomposition : $\left(\widetilde{h}_{u_1}, \widetilde{h}_{u_2}\right) \to \varphi_2$
3. First-order derivation : $\varphi_2 \to \dot{\varphi}_2$
4. Threshold-crossing detection : $(-\dot{\varphi}_2 \geq th_\omega) \to mswTick$.
5. Local minima detection before, resp. after, mid-swing events : $MSW_n \to TO_n$, HS_{n+1}.

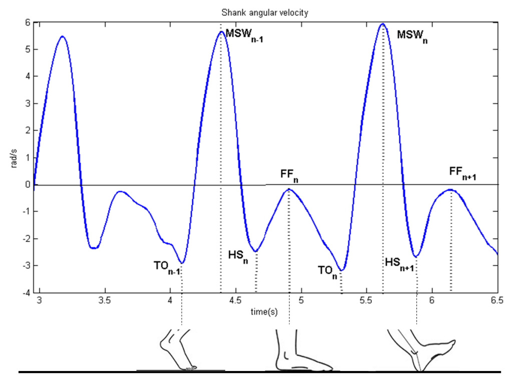

Figure 2: Gait event detection : Temporal definition of heel-strike (HS), foot-flat (or mid-stance) (FF), toe-off (TO) and midswing events (MSW).

2.2 Feature extraction

Without loss of generality, suppose that we have identified both the beginning and end of a stride. The n-th stride is thus delineated by the following time sequence $[HS_n, FF_n, TO_n, MSW_n, HS_{n+1}]$ from which temporal gait parameters are easily deduced, See Fig.2. Swing duration is thus given by $T_{SW} = HS_{n+1} - TO_n$.
We propose in Algorithm 2 a simple yet effective method to evaluate vertical and horizontal displacement during a stride. For a given stride, we first project acceleration in the magnetic inertial frame (p_1, p_2) .

$$\begin{pmatrix} a_{p_1} \\ a_{p_2} \end{pmatrix} = \begin{pmatrix} \cos\varphi_2 & \sin\varphi_2 \\ -\sin\varphi_2 & \cos\varphi_2 \end{pmatrix} \begin{pmatrix} a_{u_1} \\ a_{u_2} \end{pmatrix} \quad (3)$$

Then we perform a simple integration on the *centered* acceleration to derive an average velocity along those (fixed) directions. The time interval that is used for integration is limited to the swing phase.

$$\begin{pmatrix} \langle v_{p_1} \rangle \\ \langle v_{p_2} \rangle \end{pmatrix} = \begin{pmatrix} \int_{T_{SW}} a^c_{p_1}(t) \\ \int_{T_{SW}} a^c_{p_2}(t) \end{pmatrix} \quad (4)$$

Displacement is finally estimated through :

$$\begin{pmatrix} d_Z \\ d_\xi \end{pmatrix} = T_{SW} \begin{pmatrix} \cos\varphi_1 & -\sin\varphi_1 \\ \sin\varphi_1 & \cos\varphi_1 \end{pmatrix} \begin{pmatrix} \langle v_{p_1} \rangle \\ \langle v_{p_2} \rangle \end{pmatrix} \quad (5)$$

In this work, the heading-dependent φ_1 angle is estimated during stance phase, when the shank is slowly varying and the measured acceleration is mainly due to gravity field. It is estimated from the components $(a_{p1}, a_{p2}) \simeq (g_{p1}, g_{p2})$ using again a Cartesian to polar decomposition.

Algorithm 2 Stride displacement estimation for the n-th stride

Input: (a_{u_1}, a_{u_2}) Acceleration in body frame (m.s^{-2})
Input: φ_1 Stride-fixed angle between (Z, p_1) axes (rad)
Input: φ_2 Stride-varying angle between (u_1, p_1) axes (rad)
Input: TO_n, HS_{n+1} Gait swing time events for n-th stride
Output: (d_Z, d_ξ) Vertical and horizontal displacement (m)

1. Project and center accelerometer components in (p_1, p_2) frame, Eq.(3).
2. Integrate acceleration during swing phase, Eq.(4). $(a_{p_1}, a_{p_2}) \to (\langle v_{p_1} \rangle, \langle v_{p_2} \rangle)$
3. Project distance in (Z, ξ) frame, Eq.(5).

The proposed feature vector Y_n includes for the n-th stride the following characteristics:

- Stride duration (s) : T_{Stride}
- Stance duration (s) : T_{ST}
- Swing duration (s) : T_{SW}
- Angular velocity at foot-flat (rad/s) : ω_{FF}
- Angular velocity at midswing (rad/s) : ω_{MSW}
- Vertical displacement (m) : d_Z
- Horizontal displacement (m) : d_ξ

3. FROM STRIDE FEATURES TO GAIT CLASSIFICATION

The second part of this algorithm consists in analysing a set of stride features to identify the gait class being performed. Our study focus on the following types of gait :

Class ω_1: level walking
Class ω_2: upslope walking
Class ω_3: downslope walking
Class ω_4: upstairs walking
Class ω_5: downstairs walking

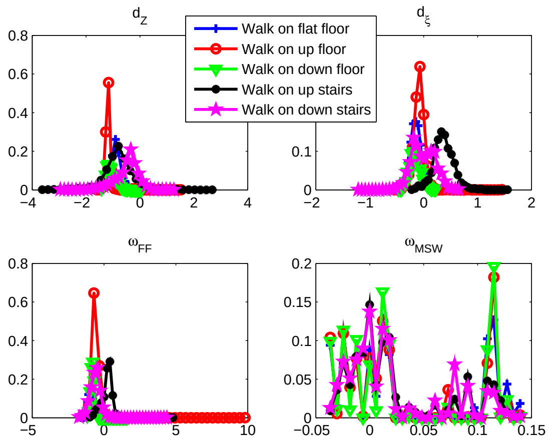

Figure 3: Probability density estimate of some stride features with respect to gait class

A rough estimation of the probability densities of the extracted features Y_n has therefore been performed and results for some of them are shown on Fig. 3. As it can be observed, the solution of the problem is not straightforward.

To tackle the gait classification issue, an algorithm based on hidden Markov models (HMMs) [2] has hence been designed. Let us recall that a HMM is a bivariate stochastic process defined by :

- A process X_n which is a Markov process and in general not observed. In the gait classification context, the random state variable X takes values in $\{\omega_1, \cdots, \omega_5\}$ so that each value corresponds to a gait class. This process is fully defined with the transition densities $a_{i,j} = p(X_n = \omega_j | X_{n-1} = \omega_i)$ which do not depend on the time index n, and the 5 initialisation probabilities $\pi_i = p(X_0 = \omega_i)$.
- A second process Y_n which is observed. The random vector variable Y_n is independent of Y_m, $m \neq n$, conditionally to X_n. It is fully defined by the probability density function (pdf) of $p(Y_n|X_n = \omega_i)$, $\forall i$. In the gait classification context, Y_n is a random vector which elements are stride features, and its state-conditional pdf is defined as a mixture of Gaussian laws which does not depend on the time index n.

If the hidden process X_n is omitted, the proposed method can be reformulated as the definition of gait-dependent pdfs. The gait classification is performed as the evaluation, at each time index, of the pdf which best fits the observation Y_n, i.e. $\omega_i^* = \arg\max_i p(Y_n|X_n = \omega_i)$. With the hidden Markov process X_n, this decision can be enforced with constraints on the hidden process transition probabilities. For a given temporal sequence of features $Y_{0:N-1} = \{Y_0, \cdots, Y_{N-1}\}$, the classification is now equivalent to compute the unobserved state sequence $X_{0:N-1}$ which maximises the following likelihood :

$$
\begin{aligned}
X^*_{0:N-1} &= \arg\max_{X_{0:N-1}} p(X_{0:N-1}, Y_{0:N-1}) &(6)\\
&= \arg\max_{X_{0:N-1}} p(X_0)p(Y_0|X_0)\Pi_{n=1}^{N-1} p(Y_n|X_n)p(X_n|X_{n-1})
\end{aligned}
$$

This kind of estimation is well known and can be performed thanks to a Viterbi algorithm (see for example [8]).

Now that the algorithm formalism has been introduced with the classification process, it remains to describe the elements of the vector Y_n and its pdf. In Section 3.1, different definitions of the vector Y_n and their pdfs are discussed. Section 3.2 is devoted to the learning process to estimate these densities using standard supervised learning techniques.

3.1 The observation vector Y_n and its modelisation

In order to evaluate which stride features, described in Section 2, are the most relevant, several subsets have been considered for the observation vector Y_n. For instance, the first set is defined as $\{d_Z, d_\xi\}$, which means that the vector Y_n is equal to : $Y_n = [d_{Z_n}, d_{\xi_n}]^T$. Different feature sets have been analysed :

- Set #1: $\{d_Z, d_\xi\}$ (displacement estimates)
- Set #2: $\{\omega_{FF}, \omega_{MSW}\}$ (angular speed estimates)
- Set #3: $\{T_{Stride}, T_{ST}, T_{SW}\}$ (time estimates)
- Set #4: Set #1 $\cup$ Set #2
- Set #5: Set #1 $\cup$ Set #3
- Set #6: Set #2 $\cup$ Set #3
- Set #7: Set #1 $\cup$ Set #2 $\cup$ Set #3

It is also necessary to define a parametric pdf for the vector Y_n which parameters depend on the hidden state.
Two models have been numerically tested and compared.
The first model $p(Y_n|X_n = \omega_i)$ is defined by :

$$p(Y_n|X_n = \omega_i) \rightsquigarrow \mathcal{N}(\mu_i, \Sigma_i) \quad (7)$$

where $\mathcal{N}(\mu_i, \Sigma_i)$ is a normal law of mean vector μ_i and Σ_i the covariance matrix (with ad-hoc sizes). For each hidden state value, $p(Y_n|X_n = \omega_i)$ is defined through the pair (μ_i, Σ_i). The second model for the state-conditional pdf of the vector Y_n is a mixture of 2 Gaussian laws defined as :

$$p(Y_n|X_n = \omega_i) \rightsquigarrow \alpha_{i,1}\mathcal{N}(\mu_{i,1}, \Sigma_{i,1}) + \alpha_{i,2}\mathcal{N}(\mu_{i,2}, \Sigma_{i,2}) \quad (8)$$

where, $\alpha_{i,1}$ and $\alpha_{i,2}$ are weight coefficients in $[0,1]$ such that $\alpha_{i,1} + \alpha_{i,2} = 1$ to ensure that $\int p(Y_n|X_n = \omega_i)dY_n = 1$.

It can be expected from the general second model to give better classification results that the first one. Nevertheless, the determination of its parameters is much more involved than for the first model, with an unknown gain on classification performances. This gain will be numerically evaluated in Section 4.2.

3.2 Probability densities estimation of Y_n

The learning process consists in estimating the parameters of the probabilistic model for each hidden state. This is mathematically equivalent to estimate for each class ω_i, the different parameters $\Theta_i = (\mu_i, \Sigma_i)$ for model #1 and $\Theta_i = (\alpha_{i,j}, \mu_{i,j}, \Sigma_{i,j})_{j=1,2}$ for model #2.

Because the hidden states are assumed known in our supervised training context, the algorithm for training the HMM output distributions is just the standard set of equations for training GMMs. It is reviewed next for self-consistency.

For the first model, the parameters estimation is straightforward with the use of the maximum likelihood (ML) estimator. Denote $S(n)$ the known (gait) state at time index n, obtained during the supervised learning stage. For gait class

ω_i, it holds

$$\begin{aligned}\mu_i &= \frac{\sum_{n=0}^{N-1} \mathbb{1}(S(n)=\omega_i) Y_n}{\sum_{n=0}^{N-1} \mathbb{1}(S(n)=\omega_i)} \\ \Sigma_i &= \frac{\sum_{n=0}^{N-1} \mathbb{1}(S(n)=\omega_i) Y_n Y_n^T}{\sum_{n=0}^{N-1} \mathbb{1}(S(n)=\omega_i)} - \mu_i^T \mu_i\end{aligned} \quad (9)$$

where $\mathbb{1}(S(n)=\omega_i)=1$ if $S(n)=\omega_i$ and 0 otherwise.

The parameters estimation of the second model is more involved with the use of the expectation maximisation (EM) algorithm [4].

3.2.1 Expectation maximisation

Consider N samples $R_{0:N-1}$ defined as independent realization of a mixture of two normal distributions.
The logarithm of its pdf equals

$$l(\Theta) = \sum_{n=0}^{N-1} \log p(R_n|\Theta) \propto \sum_{n=0}^{N-1} \log\left(\sum_{j=1}^{2} \alpha_j \tau_n(j)\right)$$

$$\text{with} \tau_n(j) = |\Sigma_j|^{-1/2} \exp(-\frac{1}{2}(R_n-\mu_j)^T\, \Sigma_j^{-1}(R_n-\mu_j)) \quad (10)$$

The problem is to estimate the set of parameters of this law $\hat{\Theta} = \{\alpha_1, \mu_1, \Sigma_1, \alpha_2, \mu_2, \Sigma_2\}$ which maximises $l(\Theta)$. Because of the sum term in the logarithm, this problem is not straightforward and the EM algorithm is used to tackle this issue [4]. Therefore a new unobserved variable Z_n, is introduced such as: $p(R_n|Z_n=j) \propto \tau_n(j)$ and $p(Z_n=j)=\alpha_j$. The joint likelihood of a sequences R_n, Z_n has the following form:

$$l(R_{0:N-1}, Z_{0:N-1}) \propto \sum_{n=0}^{N-1}\sum_{j=1}^{2} \mathbb{1}(Z_n=j) \log \tau_n(j)$$

As the process Z_n is not observed, $l(R_{0:N-1}, Z_{0:N-1})$ can not be directly maximised. The EM idea is to maximise instead the expectation of this function : $\mathbb{E}_{Z|R} l(R_{0:N-1}, Z_{0:N-1})$. To be computed, this expectation needs to know the set of parameters Θ which is unavailable. Hence the idea of EM algorithm is to fix a first set of parameters, and make it iteratively evolve to the correct one.
Denote $\Theta^{(k)}$ the set of parameters at k-th iteration and $\tau_n^{(k)}(j)$ the associated pdf using Eq.(10).
The two steps are the following ones:

1. Compute for the set of parameters $\Theta^{(k)}$:

$$Q(\Theta|\Theta^{(k)}) = \mathbb{E}_{Z|\Theta^{(k)}} l(R_{0:N-1}, Z_{0:N-1})$$

2. Estimate the set $\Theta^{(k+1)}$ which maximises $Q(\Theta|\Theta^{(k)})$.

After some calculations, this leads to update formulae:

$$\begin{aligned}\alpha_j^{(k+1)} &= \frac{\sum_{n=0}^{N-1} \tau_n^{(k)}(j)}{\sum_{n=0}^{N-1}\sum_{j=1}^{2} \tau_n^{(k)}(j)} \\ \mu_j^{(k+1)} &= \frac{\sum_{n=0}^{N-1} \tau_n^{(k)}(j) Y_n}{\sum_{n=0}^{N-1} \tau_n^{(k)}(j)} \\ \Sigma_j^{(k+1)} &= \frac{\sum_{n=0}^{N-1} \tau_n^{(k)}(j) Y_n Y_n^T}{\sum_{n=0}^{N-1} \tau_n^{(k)}(j)} - \mu_j^{(k+1)} \left(\mu_j^{(k+1)}\right)^T\end{aligned}$$

3.2.2 EM for the second model parameters estimation

In gait recognition problem, the parameters of the mixture of Gaussian laws have to be estimated for the different gait types. The above results directly apply taking in account into the sum only the terms corresponding to the gait of interest. One iteration of the learning process is summarized in the Algorithm 3 for the second model.

Algorithm 3 k-th iteration of learning algorithm

1: Compute, $\forall (i,j)$, $\tau_n^{(k)}(i,j)$:

$$\tau_n^{(k)}(i,j) = \frac{\exp\left(-\frac{1}{2}(Y_n-\mu_{i,j}^{(k)})^T \left(\Sigma_{i,j}^{(k)}\right)^{-1} (Y_n-\mu_{i,j}^{(k)})\right)}{|\Sigma_{i,j}^{(k)}|^{1/2}}$$

2: Compute, $\forall (i,j)$, $\lambda_n^{(k)}(i,j) = \mathbb{1}(S(n)=\omega_i)\tau_n^{(k)}(i,j)$

3: Update formulas:$\forall (i,j) \in \{1,\cdots,5\} \cup \{1,2\}$

$$\begin{aligned}\alpha_{i,j}^{(k+1)} &= \frac{\sum_{n=0}^{N-1} \lambda_n^{(k)}(i,j)}{\sum_{n=0}^{N-1}\sum_{j=1}^{2} \lambda_n^{(k)}(i,j)} \\ \mu_{i,j}^{(k+1)} &= \frac{\sum_{n=0}^{N-1} \lambda_n^{(k)}(i,j) Y_n}{\sum_{n=0}^{N-1} \lambda_n^{(k)}(i,j)} \\ \Sigma_{i,j}^{(k+1)} &= \frac{\sum_{n=0}^{N-1} \lambda_n^{(k)}(i,j) Y_n Y_n^T}{\sum_{n=0}^{N-1} \lambda_n^{(k)}(i,j)} - \mu_{i,j}^{(k+1)} \left(\mu_{i,j}^{(k+1)}\right)^T\end{aligned}$$

Note that the EM algorithm is sensitive to its initialisation set of parameters. This point is not detailed in this paper because of the lack of space. Note also that Baum Welch algorithms are usually used to train hidden Markov models [8]. It has not been used in this context since we do not want the model to be adapted to the performed path through the transition probability of the process X_n. Furthermore, concerning the learning of the probabilities $p(Y_n|X_n=\omega_i)$, the Baum Welch algorithm is also an EM algorithm where the unobserved variable is the hidden state. In this context, the hidden state is known on the training sequences $S(n)$, so Baum Welch is also not adequate to learn these probabilities.

4. RESULTS

To enforce a stable classification along time, the probability to remain into a given state $a_{i,i}$ is set to 0.99 $\forall i$, and the transition probabilities $\forall j \neq i$, $a_{i,j} = 0.01/4$, cf. Section. 3.

4.1 Performance evaluation method

9 sequences have been provided by the CHU of Saint-Etienne. They correspond to recordings obtained for 9 different users walking a pre-defined path scenario that comprises different gait classes. Denote by U the number of training sequences and denote by V the number of test sequences. The performance of the algorithm for the #v-test sequence is obtained by comparing the temporal sequence of gait classes returned by the HMM algorithm $\{X_v^*\}_{0:N_v-1}$ and the reference sequence $S_v(n)$, annotated by the medical team for this test sequence. It is important here to note that although the model

learning is done by concatenating the U sequences into a single one, the classification performance is assessed on the V distinct stride sequences. Our performance criterion will be the good detection rate defined by:

$$J = \frac{1}{V}\sum_{v=1}^{V}\frac{1}{N_v}\sum_{n=0}^{N_v-1}\mathbb{1}\left(S_v(n) = \{X_v^*\}_n\right)$$

For a perfect classification, $J = 1$.

4.2 Choice of observation vector and its modelisation

The objective of the first numerical simulation is to estimate numerically the impact of the chosen feature set and also the best vector model for Y_n. The learning process has therefore been performed on the 9 sequences (one common model for the 9 persons), and validated afterwards on **the same** 9 sequences. The results are shown on Table 1. For the model #1, 7 features are required to have a good detection rate higher than 90%. For the model #2, despite a more involved learning process, a good classification rate higher than 90% is reached for most of the features set. Note also that for this last model, the feature sets #1, #5 and #7 gives the 3 best classification rates.

	Model #1	Model #2
Feature Set #1	87.13 %	92.21 %
Feature Set #2	63.83 %	69.79 %
Feature Set #3	70.92 %	91.46 %
Feature Set #4	89.81 %	91.66 %
Feature Set #5	82.18 %	95.53 %
Feature Set #6	89.79 %	93.82 %
Feature Set #7	93.66 %	98.66 %

Table 1: Good classification rate with respect to the observation set and its modelisation

4.3 Impact of training sequence length

The objective of the second numerical simulation is to evaluate the impact of the number of training sequences needed for learning. In this context, the learning has hence been performed on U sequences, and the validation is done on the $V = 9 - U$ remaining sequences. For each possible value of U, $\binom{9}{U}$ sets of training sequences can be used. The performance criterion is thus an average of the criterion value J estimated for each configuration of the training sequences.

Concerning the vector Y_n, the model #2 has been used with the set of features #1, #5 and #7. The results are presented on Fig.4. The set #1 has a good classification rate which tends to 90% and can be learnt with only 1 sequence. The set #5 can also be learned with a few training sequences but seems to be very user sensitive since the performance curve is not increasing. Finally, the set #7 leads to good classification rate if 4 training sequences at least are used to perform the training.

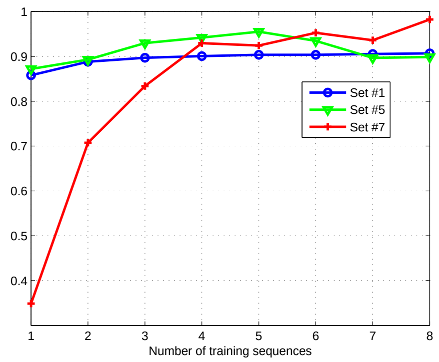

Figure 4: Classification performances with respect to the number of training sequences U

5. CONCLUSION

This paper demonstrates that combined 3-D magnetometer and accelerometer can be used for good-performance HMM gait classification. Comparison against the gait classification performances of other relevant sensor types and other classification techniques is a topic of further research.

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