Detection and characterization of gait modifications, for the longitudinal follow-up of patients with neurological diseases, based on the gait analyzing system *GAIMS*

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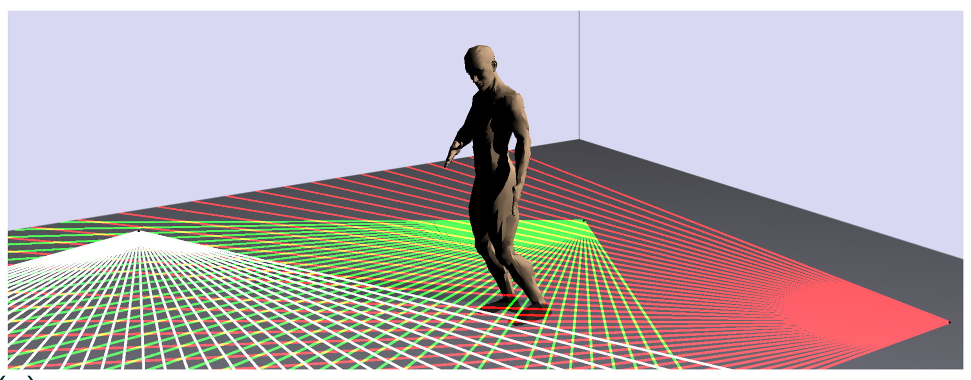
Introduction

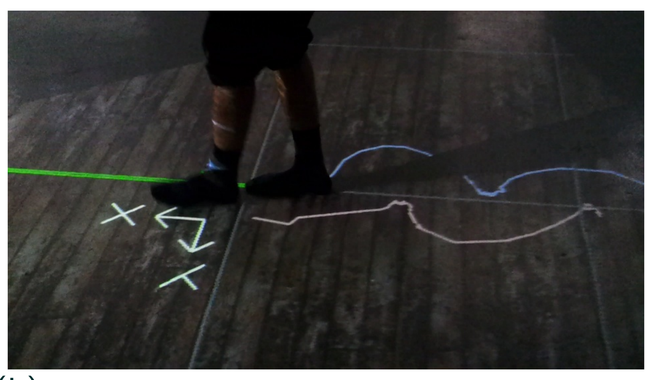
The clinical evaluation of the ambulation impairments is useful for the detection of neurological diseases such as multiple sclerosis (MS) and for the follow-up of patients. Most of the patients with MS have walking difficulties and they often perceive these difficulties as the most important source of disability [1]. Moreover, ambulation impairments appear during the early stages of the disease and the magnitude of the gait modification is a good indicator of the disease activity. Therefore, the clinical evaluation of the gait can help to know if the drugs and rehabilitation methods have a positive effect.

Often, the examination of the patient's ambulation impairments is not instrumented at all, or the measures are very limited, because of the constraints of clinical routine. In the case of MS, clinicians mostly focus on a velocity measurement. Such tests are limited since no relevant conclusion could be drawn on the evolution of MS if the speed evolution between two consecutive visits is less than about 20% [2, 3]. Thus, we need more information.

GAIMS [4, 5] is a multidisciplinary project involving engineers from the University of Liège and neurologists from the University Hospital of Liège. Its goal is to develop a new gait measuring system designed to meet the clinical routine constraints and to overcome the previous limitations by measuring a large variety of gait characteristics (26 for now). It measures the lower limbs extremities (denoted "feet" hereafter) trajectories with range laser scanners placed in the corners of the examination room, and derives the speed, the inter-feet distance, the deviation from the followed path, the cadence, the stride length, the gait asymmetry, the temporal variability, the proportion of double limb support time, *etc.* *GAIMS* is insensitive to the lighting conditions. It does not require the patient to be equipped with any marker or sensor, and it analyzes both the swing and the stance phases. We also develop methods that help to interpret the measures taken by *GAIMS*. This poster focuses on the longitudinal follow-up of MS patients.



(a) We measure feet trajectories with range laser scanners covering a common horizontal plane located at the height of the ankles. A few laser beams are depicted for three sensors, even if they are invisible in reality.



(b) This picture shows the path followed by the patient in green, and the measured feet trajectories projected in real-time on the floor using a beamer.

Figure: Principle of the gait measuring system *GAIMS*.

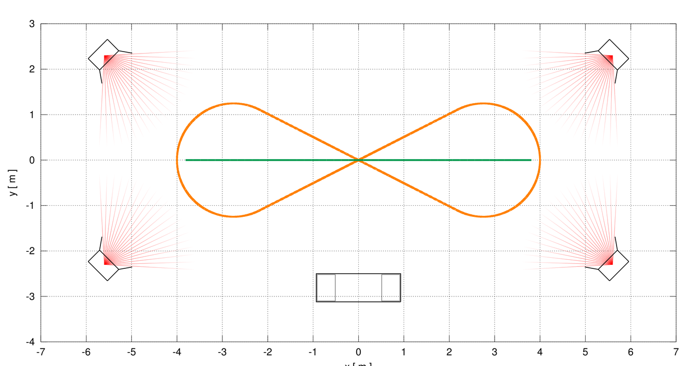
This work extends [6]. We develop a cascade of two automatic tools to help neurologists interpreting the evolution of the gait characteristics measured by GAIMS between two consecutive visits of the same patient. The first one indicates if there has been a significant gait modification, while the second one aims at specifying its direction (reduced or amplified gait impairment). Both tools are based on a machine learning technique [8], as in [6].

Protocol followed during the data acquisition

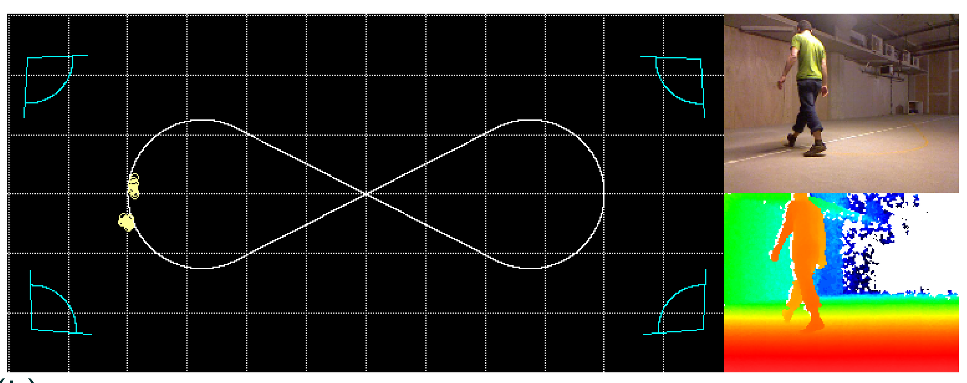
Three walking modes are analyzed (preferred pace, as fast as possible, and tandem gait) on a 25ft straight path, and on 20m, 100m, and 500m (several laps of a 20m ∞-shaped path).

	test	1	2	3	4	5	6	7	8	9	10	11	⟷	12	13	14	15	16	17	18	19	20	21	22
distance	25 Ft	•	•	•	•	•	•						rest period with or without alcohol intake	•	•	•	•	•	•					
	20 m							•	•	•										•	•	•		
	100 m										•	•											•	•
mode	comfortable	•	•					•			•			•	•					•			•	
	fast			•	•				•			•				•	•				•			•
	tandem					•	•			•								•	•			•		

Table: The acquisition protocol consists in a pair of two consecutive visits, each with 11 walking tests. The rest period between the two visits lasted 30 minutes for the volunteers who drunk alcohol, to reach the peak blood alcohol concentration. For the others, the rest period lasted at most 2 hours.



(a) The straight path and the ∞-shaped path (followed by the patients during their examination) are depicted in green and orange, respectively.



(b) Left: the four sensors depicted in turquoise and the horizontal cross-section of the walking person's legs in yellow. Right: Synchronized color and range images acquired by a kinect (unused).

Figure: Map of the acquisition room.

Obtaining the learning and testing samples with healthy people

The two tools developed in this work are binary classifiers applicable on any pair of consecutive visits. These classifiers are learned from a few pairs given as training examples.

To gather the pairs of two consecutive visits without any gait modification, we asked 27 healthy persons to perform the protocol shown above, with a maximum of 2 hours between the two visits. A short rest period has been forced between the two visits in order to avoid fatigue and to soften the effects related to the test-retest phenomenon. All tests were recorded with *GAIMS*, the feet trajectories were computed with the processing pipeline presented in [7], and 26 gait descriptors were computed for each test.

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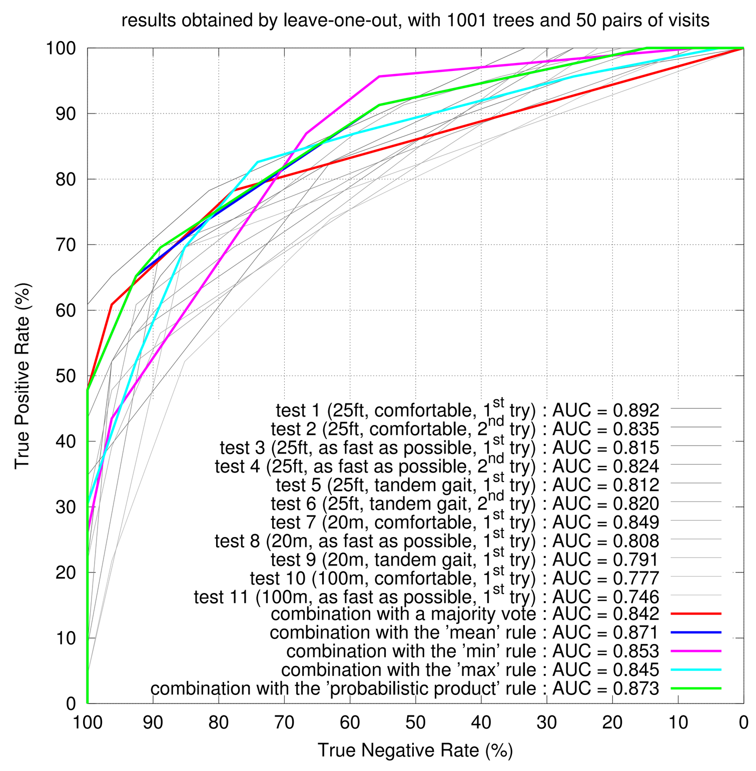
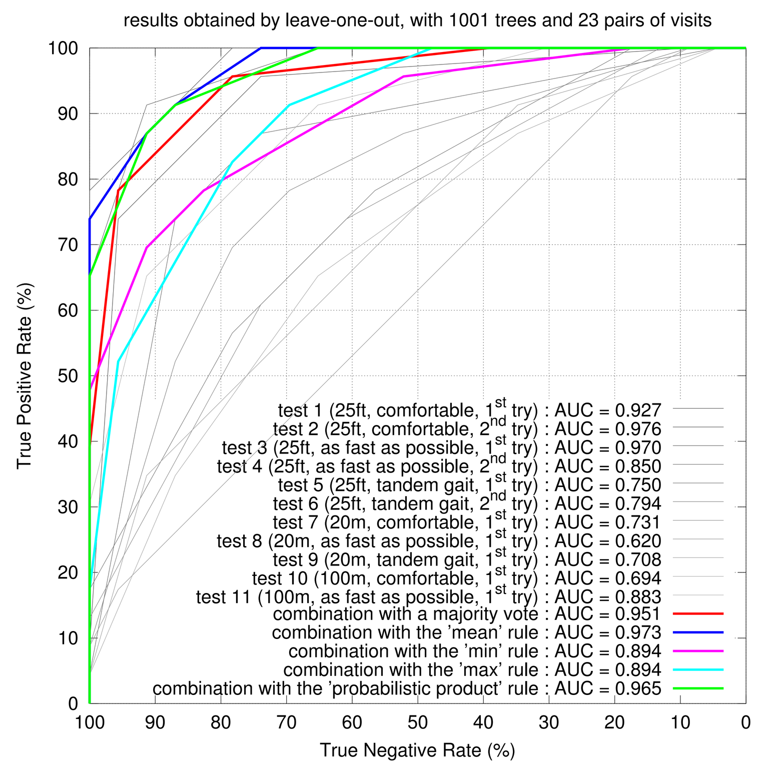
As in [6], the pairs with a gait modification have been obtained, for practical reasons, by inducing ataxia in 23 healthy subjects with alcohol in their second visit. Note that cerebellar ataxia is known to be a major component of the gait impairments in MS. For the pairs of tests in which the first one was recorded before alcohol intake and the second one after it, we expect to have an amplified gait impairment. The pairs for which the impairment is reduced are obtained by swapping the two visits in the previous pairs. We tried to reach the same peak blood alcohol concentration (BAC) for all participants, using a normogram related to the gender and the weight. As the mean BAC (measured with a breathalyzer) is $67\,mg/l$, the most important modifications are behavioral. The gait disorder specialists present during the acquisitions had difficulties to see any difference on feet movements induced by ethanol. Therefore, the gait modifications considered in this work are weak.

Results

Our results have been obtained by *leave-one-out*, and with the *ExtRaTrees* [8]. The attributes describing the pairs of tests are inspired by [6]. We learn two models (classifiers): one predicting the probability of gait modification based on any pair of tests and the other one predicting the probability of gait improvement, assuming a gait modification. We apply a correction to the output to compensate for the imbalanced learning sets [9].

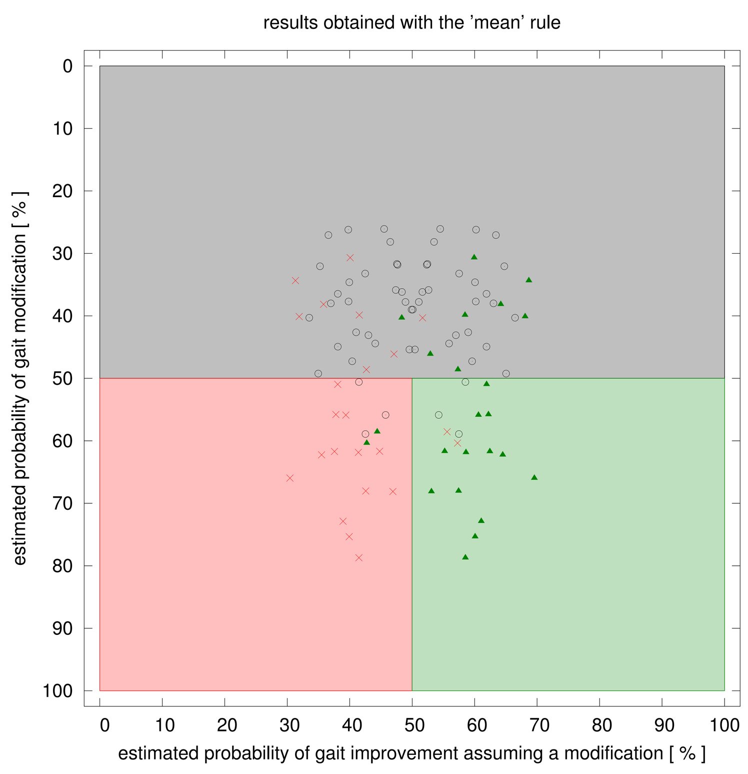


(a) Classifier predicting the probability of gait modification.



(b) Classifier predicting the probability of gait improvement.

Figure: Results of the two classifiers developed in this work, plotted as ROC curves, with repaired concavities [10, 11]. We assess the models on each of the 11 types of pairs of tests (*e.g.* $(test_1, test_{12})$, $(test_2, test_{13})$, ...) separately, and investigate 5 strategies [12, 13] for combining the probabilities predicted for the eleven pairs of tests. Note that all types of pairs of tests always feed the learning.



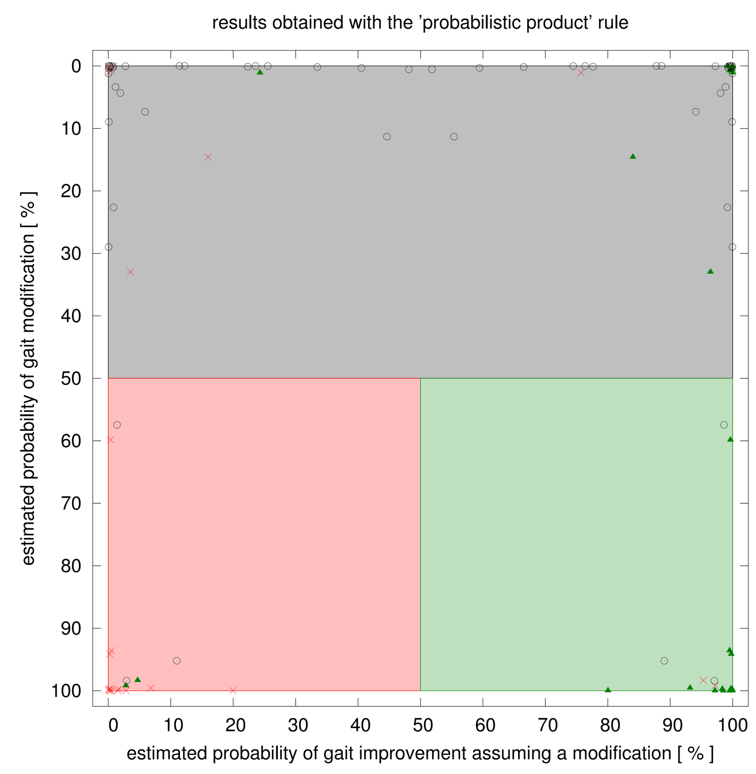


Figure: Results obtained after combining the probabilities predicted by the two classifiers, for two combination strategies. Red, black, and green dots correspond to the real classes "gait deterioration", "no modification", and "gait improvement", respectively. The pink, gray, and light green areas correspond to the cases in which the cascade of the two classifiers predicts "gait deterioration", "no modification", and "gait improvement". In each area, the majority of the points are correctly classified, indicating the merits of our approach.

Conclusion

With the quantitative and objective gait characteristics measured by *GAIMS*, it is possible to help the neurologists in the follow-up of their patients with neurological diseases in which there is some ataxia, such as the multiple sclerosis. We have developed a cascade of two binary classifiers in order to discriminate between the three classes "gait deterioration", "no modification", and "gait improvement".

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