Sensor-based Pattern Recognition Identifying Complex Upper Extremity Skills

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1 OBJECTIVES

Objectively quantifying actual arm-hand performance is very important to evaluate arm-hand therapy efficacy in patients with neurological disorders. Currently, objective assessments are limited to evaluation of 'general arm hand activity', whereas monitoring specific arm-hand skills is not available yet. Instruments to identify skills and determine both amount and quality of actual arm-hand use in daily life are lacking, necessitating the development of a new measure. To identify skills, pattern recognition techniques can be used. Commonly used pattern recognition approaches are: statistical classification, neural networks, structural matching and template matching (Jain et al., 2000). The latter is used in the present study, aiming to provide proof-of-principle of identifying skills, illustrate this for the skill drinking in a standardized setting and daily life situation in a healthy subject.

2 METHODS

Four sensor devices, each containing a tri-axial accelerometer, tri-axial gyroscope and tri-axial magnetometer were attached to the dominant hand, wrist, upper arm and chest of participants. Thirty healthy individuals performed the skill drinking 5 times in a standardized manner, i.e. with similar starting position and instruction about how to perform the skill. In addition, for one person a 30 minute registration in daily life including multiple skills (of which 4 times the skill drinking) was made.

Signals were filtered with a 4^{th} order zero-time lag low-pass Butterworth filter (cut off frequency: 2.5 Hz). Data analysis consisted of the following steps: 1) temporal delimitation of each of the five attempts of the skill drinking, i.e. identifying the start and endpoint of each attempt recorded; 2) normalization of the signals in the time domain in order to correct for (small) variations due to differences in speed of task execution; 3) averaging signal matrices from the five attempts of each individual person to obtain the individual template, i.e. the underlying ensemble averaged signal matrix per task per individual; averaging signal matrices from the individual templates of multiple persons, to create a generic template; 4) identification of dominant sub phases of templates, within a specific task, using Gaussian-based linear envelope decomposition procedures; 5) recognition of specific skill execution among various skills performed daily, i.e. searching for template occurrence among signal recordings gathered in a standardized setting and a daily life condition, using feature extraction and pattern recognition algorithms based on 2D convolution. Cross-correlation coefficients were calculated to quantify goodness-of-fit.

3 RESULTS

Performance of the skill drinking was identified unambiguously (100%) in de standardized setting (figure 1a). For the templates consisting of the complete skill, mean cross-correlation was 0.93 for the individual template and 0.79 for the generic template. For the templates consisting of sub-phases, mean cross-correlations ranged between 0.89 and 0.99 for the individual template and between 0.78 and 0.86 for the generic template.

In the daily life registration, all instances at which drinking was performed, were recognized with the template consisting of the complete skills (mean cross-correlation: 0.51) (figure 1b). However, also five false-positive findings were present (mean cross-correlation: 0.46). Using the template consisting of the sub phases, in general the skill

Lemmens R., Janssen-Potten Y., Timmermans A., Smeets R. and Seelen H..
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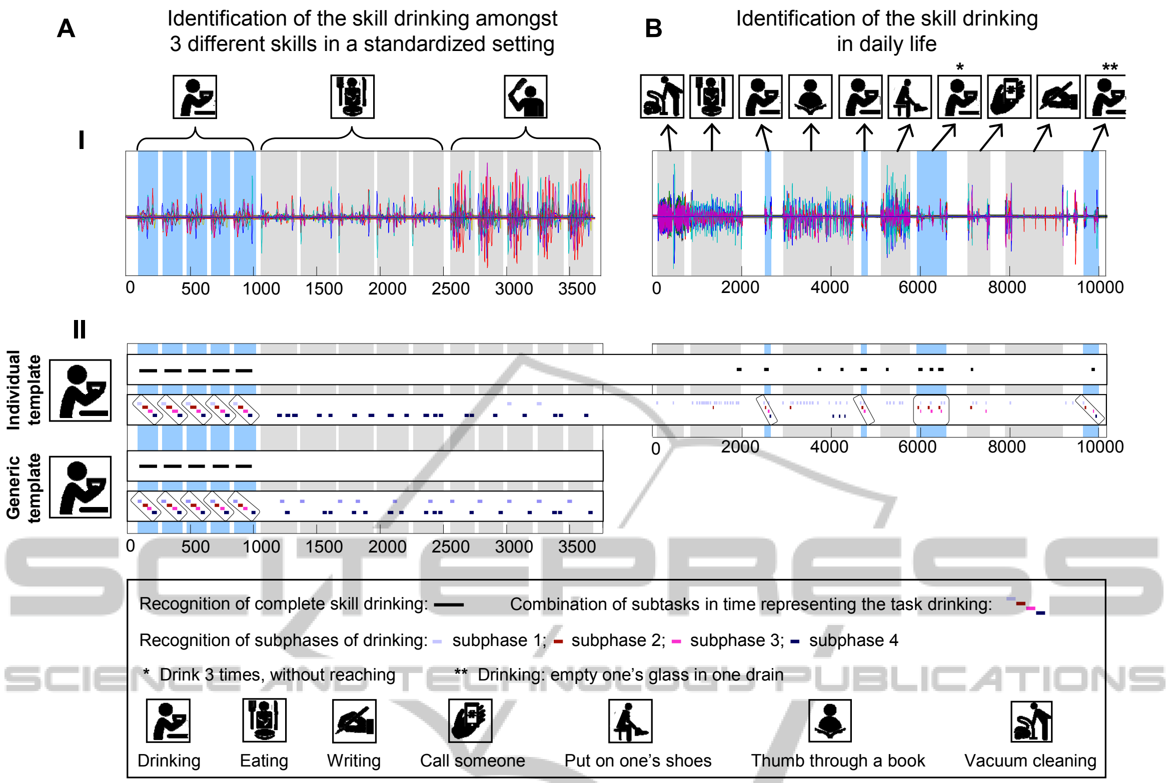

Figure 1: Identification of the skill drinking in a daily activity registration in a standardized setting (A) and daily life setting (B). Panel I displays the superimposed signals (36 in total) of a registration of an individual during the execution of several skills. Panel B displays the pattern recognition using a individual and a generic template for the skill drinking. Both pattern recognition with the complete skill as template and skill sub phases as template are shown. The black lines (complete skill) and coloured lines (skill sub phases) in panel II mark the places were the template is recognised in the longer registration.

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drinking was identified (cross-correlation ranging between 0.62 and 0.82), but some sub phases were not recognized correctly. A false-positive finding occurred frequently for sub phase 1 and sporadic for the other sub phases (mean cross-correlation between 0.55 and 0.92). Regarding the combination of sub phases, no false-positive findings were found.

4 DISCUSSION

Using this method, it is possible to identify a specific skill amongst multiple skills, both in a standardized setting and in a daily life registration. The long-term aim is to use this method to a) identify which arm-hand skills are performed during daily life by individuals, b) determine the quantity of skill execution, i.e. amount of use, and c) determine the quality of arm-hand skill performance. At the moment, as far as we know, no such instrument is available. There are however many instrument being developed using many different pattern recognition techniques. Leutheuser et al, for example, used a feature set of four time domain features and two frequency domain features and a combination of classification systems to distinguish between activities like vacuuming, sweeping, sitting, standing, bicycling, ascending/descending stairs and walking (Leutheuser et al., 2013). Future research will firstly focus on optimizing the method described in this study, and thereafter focus on applying this method for more skills, in neurological patients and in natural living situations.

REFERENCES

Jain A.K., Duin R.P.W. and Mao J. (2000) Statistical Pattern Recognition: A Review. *IEEE Trans Pattern Analysis and Machine Intelligence,* 22.

Leutheuser H., Schuldhaus D. and Eskofier B.M. (2013) Hierarchical, Multi-sensor based Classification of Daily Life Activities: Comparison with State-of-the-art Algorithms using a Benchmark Dataset. *PlosOne,* 8
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