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USING A SELF-ORGANIZING MAP TO IDENTIFY GROUP-SPECIFIC MOVEMENT PATTERNS DURING RUNNING

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The purposes of this study were (a) to use a self-organizing map to identify groups of people with a similar movement pattern, (b) to associate these groups with characteristics related to age and gender, and (c) to investigate whether these groups require specific footwear features to improve comfort. The movement patterns of 88 subjects during 5 running trials were collected. A self-organizing map was used to identify groups with group-specific movement patterns. The identified groups had specific footwear requirements with respect to comfort, which was only partially explained by the age characteristics of these groups. This study demonstrated how groups of people with specific needs regarding footwear comfort can be identified by their movement pattern.

KEY WORDS: functional groups, self-organizing maps, kinematics, running

INTRODUCTION: Characteristics, such as age (Fukuchi & Duarte, 2008), gender (Nigg et al., 2012), and anthropometric features (Williams et al., 2004) are assumed to be reflected in human movement patterns. Therefore, people with similar characteristics are expected to have a similar running movement pattern. Previous research has provided strong evidence that groups of people with a similar movement pattern, called ‘functional groups’, require group-specific footwear features for (a) improving footwear comfort, (b) optimizing movement performance, and (c) reducing injuries as they are prone to similar movement-related injuries (Nigg, 2010).

In order to address the specific needs of functional groups, one must first identify the different functional groups by their movement patterns. Standard analysis tools commonly applied in biomechanics cannot be used to identify group-specific movement patterns, as these analysis tools: (1) use discrete data, and (2) require predetermined groups to be able to identify group-specific movement patterns. The use of discrete data assumes that everything measured, except a few data points, is not of importance. Since there is no evidence for this assumption, important data that may identify group-specific movement patterns may be missed. Consequently, continuous data should be used including all measured data. When using predetermined groups (e.g. certain age groups, gender groups) one assumes that these groups are the most important ones with respect to group-specific movement patterns. Since there is no evidence for this assumption, groups of people with unknown similarities in their characteristics might not be identified. Recently, analysis tools based on unsupervised pattern recognition algorithms (e.g. self-organizing maps) were introduced to biomechanics (Janssen et al., 2011; Lamb et al., 2011a). These analysis tools can analyse continuous data sets and do not require predetermined groups to identify group-specific movement patterns.

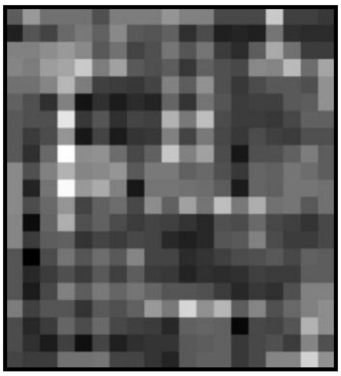
Therefore, the purposes of this study were (a) to use a self-organizing map (SOM) to identify groups of people with a similar movement pattern, (b) to associate these groups with characteristics related to age and gender, and (c) to investigate whether these groups require specific footwear features to improve comfort.

METHODS: Kinematic data of 88 healthy subjects (age range: 16-76 years; average age: 39.6 SD 19.6 years; 45 males, 43 females) during 5 over-ground running trials (3.33 ± 0.16 ms^{-1}) were collected. The kinematic data were collected using a 3D motion capture system (Motion Analysis Corp., USA) and 12 retro-reflective markers. The markers were skin-mounted on the right and left anterior superior iliac spine, on the lower back, on a distal, medial and proximal part of the right thigh and shank as well as on a low, high and

lateral position of the right rear foot. A neutral running shoe with medium midsole hardness was provided to each subject.
The continuous 3D coordinates of the 12 markers of the stance phase of each running trial were reconstructed using EVaRT (Motion Analysis Corp., USA). The marker coordinates were normalized to the duration of the stance phase (0-100 %, i.e. 101 data points) and to the static height of each subject. The 3D coordinates of the 12 markers for one trial were vectorized to a 3636 dimensional row vector (12 markers x 3 dimensions x 101 data points). A data matrix was created composed of the row vectors of each trial of each subject (5 trials x 88 subjects), yielding a matrix dimension of 440 x 3636.
SOMs are special types of artificial neural networks that are beneficial when it comes to biomechanical studies with pattern recognition questions (Janssen et al., 2008; Lamb et al., 2011b). A 2-stage procedure was conducted to identify the groups with the group-specific movement patterns by means of the SOM. This 2-stage procedure was found to be beneficial when compared to direct clustering (Vesanto & Alhoniemi, 2000). In the first stage, the SOM was applied on the data matrix. The following SOM settings were used: 11 x 10 map units, linear initialization algorithm, batch trainings algorithm, and Gaussian neighbourhood function. The SOM was utilized by means of a SOM Toolbox (Kohonen, 2009). In the second stage, a *k*-means clustering algorithm was applied on the SOM outcome to cluster the group-specific movement patterns. Since the *k*-means clustering algorithm required a predetermined number of groups to be identified, different numbers of groups (2-10 groups) had to be tested with respect to the quality of the grouping. The quality of the grouping was determined by an assessment and classification rate. The assessment rate is an average percentage value for the number of trials of a single subject that are assigned to the same group. The classification rate is an average percentage value that shows whether the different groups were sufficiently separated to assign a new subject, based on its movement pattern, to one or the other group. The group number with the highest average value of the assessment and classification rate was considered for further analysis. The average age and the gender composition of each group were determined. Significant differences in the average age between the groups were investigated using a One-way ANOVA and a Post Hoc Test with Bonferroni correction (p=.05). To determine whether these groups require specific footwear features to improve comfort, the comfort preferences of each group were compared. For this purpose, the preferred shoe condition (out of 3 possible conditions: soft, medium, and hard midsole) was revealed for each subject.

RESULTS: Figure 1a shows the outcome of the SOM, presented by a unified distance matrix (U-Matrix). Dark squares on the U-Matrix represent clusters of similar running trials or movement patterns, respectively. The white squares indicate the borders between the clusters. Therefore, the U-Matrix provides a visual estimation of the potential groups of people with similar movement patterns. The visual investigation of the U-Matrix showed small clusters equally distributed over the U-Matrix (Fig. 1a). Figure 2 displays the assessment and classification rate for the different numbers of groups.

(a)



(b)

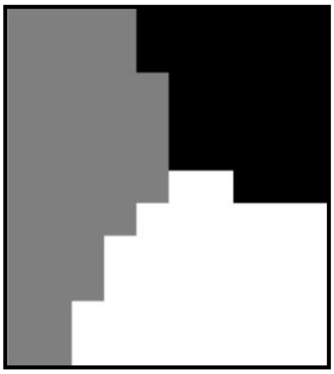


Figure 2: (a) U-Matrix that provides a visual estimation of the potential groups with specific movement patterns. Dark squares on the U-Matrix represent clusters of similar movement patterns and white squares indicate the borders between the clusters. (b) Regions of the U-Matrix that were clustered together. Each colour (black, grey, and white) represents one group.

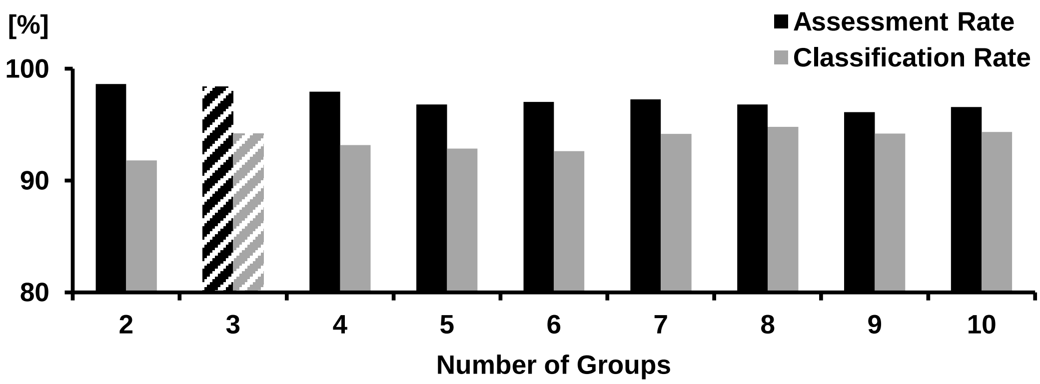


Figure 3: Assessment and classification rate for different numbers of groups. The striated bars indicate the group number that was considered for further analysis.

The highest assessment rate was achieved with 2 groups (98.6 %) and the highest classification rate was found with 8 groups (94.8 %). However, calculating the average of the assessment and classification rate revealed that the highest value was achieved with 3 groups (96.3 %). Figure 1b shows the regions of the U-Matrix that were clustered together by the *k*-means clustering algorithm. Each of these 3 different regions (black, grey, and white) represents a group with a group-specific movement pattern. A significant difference ($p<.05$) between the average age of Group 1 (45.4 years) and the average age of Groups 2 (38.2 years) and 3 (34.8 years) was found (Fig. 3a). The gender composition (Fig. 3b) showed only small differences between the number of males and females in each group. Figure 3c shows how many subjects in each group preferred the soft, medium or hard midsole. It could be seen that the medium midsole in Group 1 and the soft midsole in Groups 2 and 3 were the most preferred shoe conditions.

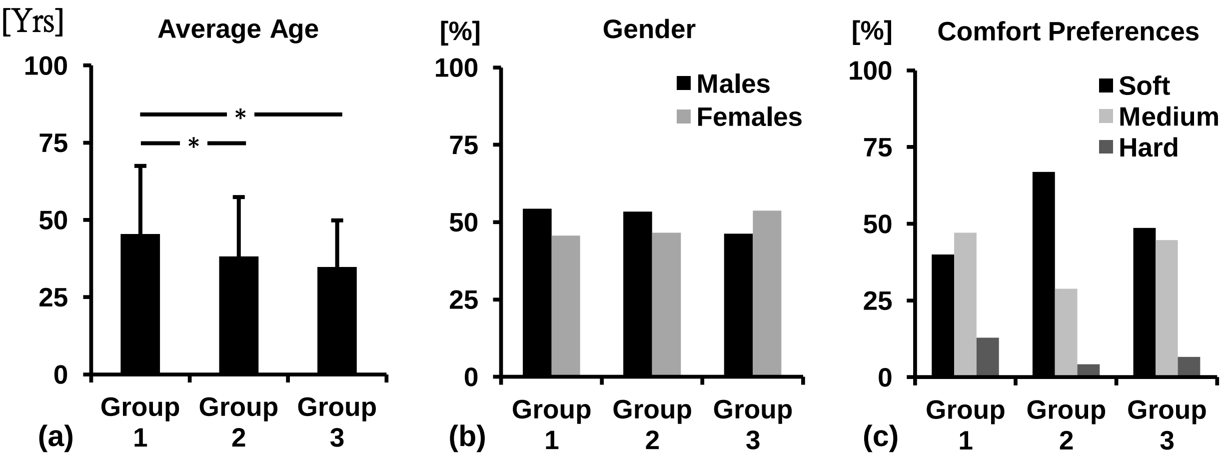


Figure 4: Groups with group-specific movement patterns: (a) average age - * indicates significant differences (*p*<.05), (b) gender, and (c) comfort preferences with respect to shoes with a soft, medium or hard midsole configuration.

DISCUSSION: The results of this study showed a significant difference in the average age between Group 1 and the other two groups. Therefore, age can be seen as an important factor that influences the movement pattern of individuals in running. The essential part of this result is that the age-dependent movement patterns were identified without using predetermined groups. Thus, one does not have to pre-group subjects based on similar characteristics in order to identify similar movement patterns. This is important when group-specific movement patterns should be identified that are based on characteristics not as obvious as age or gender. For instance, it was revealed that Group 2 and Group 3 have a different movement pattern. Since there are hardly any differences in the age and gender characteristics between these two groups, the characteristic that separates these groups is unknown. Therefore, predetermined groups based on age or gender cannot be used to identify the group-specific movement patterns of Groups 2 and 3.

The identification of groups with a group-specific movement pattern is important in order to investigate the specific needs of functional groups with respect to footwear. It was shown that Group 1, being the oldest subject group, was the only group where the medium midsole was the most preferred midsole configuration. This might be explained by the observation that elderly people prefer in general harder shoes as they provide more stability (Nigg & Skleryk, 1988; Robbins et al., 1992). Differences in the comfort preferences were also obtained between Group 2 and Group 3. These group-specific needs would not have been revealed without separating Group 2 and 3 based on their movement pattern. This example emphasises the importance of the proposed analysis approach in order to be able to address the group-specific needs of functional groups with respect to footwear.

After identifying groups with specific movement patterns, future studies should aim to determine the actual differences between the group-specific movement patterns. In addition, one should also gain a better understanding about the characteristics that cause the group-specific movement patterns.

CONCLUSION: There exist groups of people with specific needs regarding footwear, which cannot be identified by obvious characteristics such as age or gender. This study used an analysis approach that is able to identify these groups by their movement patterns. Being able to identify groups with group-specific movement patterns is essential in order to find the footwear features that can benefit these groups of people.

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