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Title Page & Abstract

Title

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Optimal Marker Set Assessment for Motion Capture of 3D Mimic Facial Movements

Abstract

Nowadays, facial mimicry studies have acquired a great importance in the clinical domain and 3D motion capture systems are becoming valid tools for analysing facial muscles movements, thanks to the remarkable developments achieved in the 1990s.
However, the face analysis domain suffers from a lack of valid motion capture protocol, due to the complexity of the human face. Indeed, a framework for defining the optimal marker set layout does not exist yet and, up to date, researchers still use their traditional facial point sets with manually allocated markers.
Therefore, the study proposes an automatic approach to compute a minimum optimized marker layout to be exploited in facial motion capture, able to simplify the marker allocation without decreasing the significance level. Specifically, the algorithm identifies the optimal facial marker layouts selecting the subsets of linear distances among markers that allow to automatically recognizing with the highest performances, through a k-nearest neighbours classification technique, the acted facial movements. The marker layouts are extracted from them. Various validation and testing phases have demonstrated the accuracy, robustness and usefulness of the custom approach.

Keywords

3D Face; Face Analysis; Motion Capture; Marker Optimization; Feature Extraction.

1 Introduction

The face is one of the most important parts of the human anatomy, as it is a huge source of information, and plays an essential role in social interaction. In fact, facial expression is one of the ways for conveying emotional messages, creating interpersonal communication and establishing links between individuals (Bargiela-Chiappini & Haugh, 2010). Muscle movements, in particular, are the key element which facial expressions rely on. Indeed, their role in the social environment of the individual is core for communication activities. However, accidents or musculoskeletal face disorders may lead to alterations in facial muscle functions, bringing to unsynchronized facial movements or even to facial paralysis; these conditions not only cause a loss of physical function but also affect the patient's social communications and interaction, damaging his wellbeing.

Hence, in these decades, the objective quantification of facial movements has acquired great importance in the clinical domain, and facial mimicry studies have been carried out embracing many applications, such as for helping maxillofacial surgery (Sforza, et al., 2010) and facial motion rehabilitation (Bajaj-Luthra, et al., 1998) (Byrne, 2004).

Currently, different methods are employed for evaluating facial muscle function. One way consists of observing their contraction, which causes local facial skin displacement and, subsequently, visible facial appearance changes, to record the clinical observations in writing and to regularly photograph facial expressions. Then, these data are analysed according to biopsychosocial aspects. In other cases, scales are used to quantify deficits, as numerous scales have been proposed (House, 1983) (Reitzen, et al., 2009) (Henstrom, et al., 2011) during the last years. However, it stills a difficult task to understand and correctly evaluate facial deficits, as it requires specific experience (Di Stadio, 2015).

Another approach to quantify facial movements is to use facial electromyography (EMG), which has been found to be a useful tool since it is sensitive even to small facial muscle changes that no visual coding technique can capture (Van Boxtel, 2010) (Gupta, et al., 2017) (Chandu, et al., 2005). However, EMG has some limitations that can reduce its effectiveness in the field of facial analysis. Firstly, the initial setup requires a significant amount of time; then, it is an invasive technique, as the connection between skin electrodes and the control device can interfere with the natural and spontaneous behaviour of the patient.

These evaluations brought the researchers to investigate other approaches such as 3D scan techniques, which have resulted to be a valid tool for evaluating facial muscle movements. In fact, these systems can be used for planning future maxillofacial surgery (Adolphs, et al., 2012), as well as for quantifying soft tissue changes (Bianchi, et al., 2012) and facial mimics' variations in patients before and after the treatment (Bianchi, et al., 2012). The facial surface data are acquired using three-dimensional scanners and the facial movements' information is described in terms of surface and landmark displacements (Sjogreen, et al., 2010). However, the main drawback of scanner systems is that they do not measure facial movements in motion (Ju, et al., 2012).

3D motion capture systems solve the previous problems. Relying on multiple external sensors (i.e. calibrated video cameras), it tracks the movements performed by a subject, equipped with a set of tiny markers placed on his face. The configuration can involve a relatively large number of markers, but it can easily change, according to the researchers' needs and goals, always permitting to the skin to move freely. The position, velocity and displacement information of the markers in the three dimensions are determined by cameras, by capturing the light reflected or emitted by the markers and using triangulation.

Several studies in the clinical field have already highlighted the potential of this technology, but, up to date, most of the researchers use their own manually placed marker configurations, which significantly vary in the total number of facial points and in their location.

Presumably, the main reason is that finding a standardized and optimal marker layout is challenging due to the anatomical complexity, large shape variation, and no rigid deformability of the human face. Moreover, choosing the correct marker displacement is not a simple task, as their number and position are directly related to the chosen application and they affect the usefulness of motion capture data. Indeed, the reliability of a motion capture analysis is directly connected to the number of available markers. Thus, dozens of markers are needed for adequately tracking the complex changes due to facial motions and skin deformations (Furukawa & Ponce, 2010). However, having an over-densely set placed in a small region also increases the redundancy in the recorded data, making it harder to capture individual markers, and unnecessarily waste technicians' time to dispose dozens of them on the facial surface.

This paper proposes an automatic approach to compute a minimum optimized facial marker layout for facial motion acquisition, choosing those that best of all permit to automatically recognise the type of movement performed. In fact, marker location and number have to be conceived in order to avoid significant loss of quality (reliability and accuracy), especially for their application in the clinical domain. Moreover, having optimized facial marker layouts will help to improve the efficiency and practicality of facial motion data in clinical applications.

The article is structured as follows. Section 2 gives an overview on the materials used. Then, it faces the developed method, used for computing novel optimized marker layouts. Section 3 provides all the layouts obtained, whereas Section 4 contain the discussion part with the satisfactory results and the currently limitation of the developed procedure. Finally, Section 5 concludes the work, providing some clues about future works and researches.

2 Materials and Methods

2.1 Protocol and Instrumentation

Fifteen healthy young adult volunteers aged from 20 to 30 years participated in this study. This study was approved by the local ethics committee (n°2011-A00532-39), was registered in clinicaltrials.gov (NCT02002572) and was performed in accordance with the ethical standards of the 1964 declaration of Helsinki. Informed consent was obtained from each subject.

As shown in Figure 1, each participant was equipped with 109 markers (Ø 1.5mm) fixed by a trained physiotherapist on the anatomical facial surface (Hontanilla & Aubá, 2008), and 3 markers pasted on a rigid structure attached on the maxilla (Rm), which represent the most reliable reference for an accurate estimation of the facial movements (Ben Mansour, et al., 2014).

<Figure 1 near here >

Every subject was asked to perform six facial expressions, later called MOUV1, MOUV2, MOUV3, MOUV4, MOUV5 and MOUV 6. These movements, shown in Figure 2, are chosen due to their great importance in the analysis of facial expression in the healthy, pathological or rehabilitative subject (Sarhan, 2017). Moreover, they take place in different zones of the face, involving both the soft tissues of the frontal and orbicular zones and the zones of the lips and the chin.

<Figure 2 near here>

Every capture, acquired through 17 optoelectronic cameras T160 and two Bonita video cameras (ViconLtd, Oxford, UK) at a recording frequency of 100Hz (i.e. at 100 frames per second (fps)), contains the 3D coordinates of facial markers. The six movements are captured separately and each movement is performed three times.

Finally, data are imported into Matlab (Mathworks, R2016a) where a custom algorithm processes and analyses the marker 3D positions.

The computer used is an HP PC, with a 2.5 GHz Intel Core i5 processor and 16 GB of RAM. The operating system is the Windows 8 version.

2.2 Problem Analysis

Since the fundamental goal of clinical facial motion analysis is to record the motion information quickly and accurately, the proposed approach identifies the optimum facial marker layout by choosing the marker setups that best permit an automatic recognition of the type of movement performed. In other words, the capacity of a set of markers to discriminate the different movements is the criterion used to quantify the goodness of a layout.

The algorithm identifies the optimal setups selecting the subsets of linear distances among markers that best allow the automatic recognition, through a k-nearest neighbours (k-NN) classification technique, of the performed facial movements. The marker layouts are extracted from them. The general structure of the algorithm is shown in Figure 3, which also underlines how each step regressively reduces the number of useful markers, up to few dozen.

< Figure 3 near here>

2.3. Data Input

Let F be the number of the frame in a facial motion capture, and N be the number of markers. Assuming $m_i \in IR^3$ is the 3D coordinate of the marker *i,* expressed in the Maxilla reference, and $m_i^{(t)} \in IR^3$ is the 3D coordinate of marker *i* at the *t* th frame. Each facial motion capture can be represented as a matrix, $X \in IR^{3N\mathrm{x}F}$, where for each marker three consecutive rows are needed for storing its position in the x, y, z reference and each column represents the displacement of one point over the time, as shown below:

$$X = \begin{bmatrix} m_{1,x}^1 & m_{1,x}^2 & m_{1,x}^3 & \cdots & m_{1,x}^F \\ m_{1,y}^1 & m_{1,y}^2 & m_{1,y}^3 & \cdots & \vdots \\ m_{1,z}^1 & m_{1,z}^2 & m_{1,z}^3 & \cdots & \vdots \\ m_{2,x}^1 & m_{2,x}^2 & m_{2,x}^3 & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ m_{N,z}^1 & m_{N,z}^2 & m_{N,z}^3 & \cdots & m_{N,z}^F \end{bmatrix}$$

2.4. Pre-processing step

As the number of markers is very high, a first selection is undertaken to reduce the dimensionality of the problem, and hence the time necessary for features' computation and subsequently selection. This reduction step aims to discard those markers that do not move during the six facial movements, and that can be considered meaningless for the movement analysis. Therefore, the trajectories study over the time (i.e. from the starting frame until the last time stamp F) is undertaken.

Examples of trajectories are shown in Figure 4.

< Figure 4 near here>

Let $\mathrm{DispVect} \in \mathrm{IR}^N$ be the vector that records the maximum displacement performed by each marker over time. The *i-th* element is calculated as

$$DispVect(i) = \max_{f=\{2,\ldots,F\}} \left[dist\left(m_i^1, m_i^f\right) \right] \qquad i = \{1, \ldots, N\}$$

where *dist* is the Euclidean distances between the marker *i* at the frame 1 and the same marker over time. This operation is done for every recording session. Then, the vectors are grouped in order to identify for each movement MOUV1, MOUV2…, MOUV6 a subset of meaningful markers.

Figure 5 is a graphical representation of the results obtained through this study.

< Figure 5 near here>

The value, in terms of mean and variation, used as a threshold (equal to 1.39 grid point, experimentally set) for identifying the points whose motion can be considered negligible, is calculated using the movement information of the markers pasted on the rigid structure, attached on the maxilla. These markers, which are considered fixed and represented the most reliable reference for an accurate estimation of the facial movements, have some natural negligible vibrations due to the global movement of the head and disentangled from the specific facial actions. Hence, the markers placed on the face, which have comparable movements, may be consider meaningless and are eliminated, in order to keep only the facial deformation for the synthesis of the rehabilitation movement.

Then, the subsets obtained for each type of movement are merged together, obtaining a set of 70 markers, shown in Figure 6.

< Figure 6 near here>

These 70 markers will be used in the subsequent phases of the algorithm, while the markers discarded during this pre-processing step will no longer be used.

Let *RadVect*∈IR^N be the array that records the maximum radial distances among those calculated over time between each off the 70 markers and the centre of the face (the marker on the dorsum of the nose, coloured in green in Figure 9). The *i-th* element is calculated as

$$RadVect(i) = \max_{f=\{1,\dots,F\}} \left[dist\left(m_i^f, c^f\right) \right] \qquad i = \{1, \dots, N\}$$

Let *DistVect*∈IR^N be the array that records the maximum linear distances among those calculated over time between each off the 70 markers and its nearest neighbours, automatically identified exploiting the Delaunay Triangulation technique. The *i-th* element is calculated as

$$DistVect(i) = \max_{f=\{1,\dots,F\}} \left[dist\left(m_i^f, m_j^f\right) \right] \qquad i = \{1, \dots, N\},\ \mathrm{j} = \{1,\dots, \mathrm{M}\}$$

with M that scans the nearest neighbours for the *i-th* marker.

2.5. Clustering step

Then, a clustering is performed, as the direct application of classification algorithm on data may not produce satisfactory results (Alapati & Sindhu, 2016).

In detail, clustering is a useful technique for finding subgroups within observations, so that objects in the same group (here called a cluster) are more similar to each other than to those in other groups. The number of expected clusters is fixed to 3, according to the structure of the data. Indeed, MOUV1-MOUV2 take place in the frontal area, whereas both MOUV3-MOUV4 and MOUV5-MOUV6 concern the mouth zone, but lips move in opposite directions for the two last movements. The three clusters are called C1, C2, and C3.

The k-means clustering algorithm is used for this task. It iteratively assigns each observation to one of the 3 groups, based on the similarity existing between the features provided. In particular, the features used for this purpose are the values recorded in *RadVect,* i.e. the radial distances between each marker and the centre of the face. As a result, the k-means clustering algorithm provides each observation with a data label (namely a clustering id), with value 1, 2 or 3 which will be used as a feature in the classification subsequent phase.

However, due to the high dimensionality of the problem, a Feature Selection Procedure is undertaken on *RadVect* before clustering. The algorithm used is the Sequential Backward Selection (SBS) algorithm, which consists of sequentially removing the least useful distances from the full set, one-at-a-time. In other words, it is a search algorithm, that is used to reduce an initial d-dimensional feature space to a m-dimensional feature subspace where $m<d$. According to the SBS algorithm, only 4 markers are needed for correctly performing the clustering phase. These markers are: the centre of the face, the marker located in the middle of the right eyebrow and the two markers on the sides of the mouth.

The motivation behind feature selection algorithms is to automatically select a subset of features that is most relevant to the problem, improving the computational efficiency by removing irrelevant features based on the cluster performance.

2.6. Classification step

Next, a classification technique is used to accomplish the task of "facial expression automatic recognition" on the six types of movement available. A classification is a form of data analysis which aims to find the model that better describes and distinguishes different data classes. The classes are six as the movements that the algorithm try to automatically recognize (MOUV1, MOUV2 MOUV3, MOUV4, MOUV5 and MOUV6). Among the many classification methods proposed by researchers, the k-nearest neighbours (KNN) algorithm is chosen due to its low calculation time and highly competitive results.

Its implemented strategy may be summarized with the sentence: "tell me who your neighbours are, and I'll tell you who you are". In more technical words, an unknown sample is classified with the most common class among k closest samples. KNN classification is in fact a two-step learning process, consisting of a training phase (where the classification model is constructed by the classification algorithm from a set of labelled samples) and testing phase (where the model is used to predict the class label for a different testing dataset, composed of unlabelled data).

Hence, the total number of the recorded motion capture sessions is split into two groups: a training dataset (80%) is used for the construction of the classification model during the training phase; a testing set (20%) is used for testing the classification accuracy of the model, when it is used with unlabelled data for predicting the class label (i.e. a value between 1 and 6 that represents the corresponding movement). Both sets are balanced according to the number of elements of each class, i.e. 80% of motion captures referring to the movement M1 stay in the training set, the other 20% in the testing set, and so on for all the 6 movements.

The input parameter k, which indicates the number of neighbours to consider for labelling the unlabelled data, has been chosen equal to 7, to avoid overfitting of the model to the training set, and this value has been used for all predictions.

The features used in this part of the procedure are the data label (namely the clustering id obtained during the clustering phase) and the values recorded in DistVect, i.e. the linear distances between each marker and its nearest neighbours.

Again, a Feature Selection Procedure is used for reducing the dimensionality problem. In this case, the Sequential Forward Selection (SFS) algorithm is applied on DistVect in order to find the subset that allows an automatic recognition of the performed movement at the fixed rate of 95%. This algorithm, unlike the SBS method, consists of adding the distances from an empty candidate subset until the addition of further distances does not decrease the criterion (i.e. the classification rate).

In addition, the procedure has been made recursive; at the beginning, the candidate subset is empty. Then, at each iteration, a new linear distance is added and a quality control is performed. If the current set of distances does not fulfil the imposed quality criterion (i.e. classification rate higher than 95%), the code continues to add new linear distances to the candidate subset. Otherwise, the solution is recorded and the procedure starts backtracking for finding other possible solutions.

Moreover, several testing/training sets are randomly created starting from the initial data, following a 20/80 partition, in order to investigate if the optimum subsets of linear distances automatically determined always lead to accurate classification results, making the procedure sounder.

Finally, the marker sets are extracted from the subsets of linear distances defined previously during the classification step.

3 Results and discussion

The results of the clustering phase are shown in Figure 7 and 8, whereas Figure 9 shows the first six optimum marker set layouts, extracted from the sets of linear distances selected by our recursive approach during the classification step after 37 hours of processing.

< Figure 7 near here >

< Figure 8 near here >

< Figure 9 near here >

Various experiments have been conducted to test and validate the optimized subsets of linear distances obtained by the automated procedure. Overall, the classification rates obtained are higher than 95% (recognition rate). These results validate the hypothesis that it is possible to select the optimal marker layouts by choosing the features that best allow for automatic recognition of the type of performed movement.

Other layouts can be found by running the algorithm longer. For the moment, these first 6 outputted marker sets have been considered adequate, since they are sufficiently different from one another, allowing clinicians to choose one layout rather than another, depending on the pathology of their patient.

The marker groups proposed contain less than 20 markers, which is a big improvement considering that the initial number of markers has been reduced by 4/5. These layouts can be used as practical guidelines for positioning facial markers, for facial movements' acquisition, especially for clinical applications.

The points' distribution on the facial surface is not homogeneous or symmetrical, as might be expected given the symmetry of the facial stimuli considered. However, this result is due to how the algorithm works. In fact, it considers each marker separately, evaluating how each point, considered alone, can improve the automatic facial expression recognition. In addition, previous studies have shown that facial expression recognition algorithms are able to function even in the presence of facial occlusions, thanks to the facial expression symmetry, which makes specular information not meaningful, or even, as shown by our algorithm, redundant.

Moreover, due to a large number of markers (109), a qualified clinician previously needed no less than 25 minutes to set up the subject. Now, the use of these new layouts considerably reduces the initial time required for the experiment setting. Moreover, tests prove that the reduction of markers still ensures an accurate quantification of the facial mimic's movement. In addition, providing different layouts, doctors have the possibility to choose the set of markers that best suits their case.
Actually, the different marker layouts provided are six. However, in the future the algorithm will be run longer in order to find more layouts, different from each other, able to adapt to a larger number of facial disorders. Indeed, different marker locations may be useful for studying different facial pathology or checking the rehabilitation degree of the specific part of the face, damaged by an injury. This way, the study will be even more focused and effective.

However, there are some limitations in the current approach. Firstly, like several other data-driven approaches, the marker layouts optimized by our algorithm rely upon the linear distances of the training facial acquisitions. Hence, if the training set is composed of a scarce variety of facial expressions and movements, the marker layouts found may not be perfectly uniformly distributed throughout the face.
At present, our training set considers a reduced number of movements in the upper and lower part of the face (natural and forced closure of the eyes, pronunciation of the sound "o" and "pu", and two types of smiles). These stimuli have been evaluated as indicative also for facial surgery by some sources (Sarhan, 2017).
Given that the purpose of the present methodology lies within the field of rehabilitation, only the stimuli related to the medical context are analysed here. However, to make these marker layouts more versatile also in other contexts, other stimuli should be considered and introduced in the training data. In a perspective of generalizability, this method with a larger training set could be used to determine the optimal position of markers able to recognize various facial expressions or action units.

Secondly, another potential issue of this approach may be the over-fitting of the feature sets to the training data such that they focus on nuances of this training set but that are not found in future samples. Finally, because the approach is designed as a recursive algorithm, finding the global optimum is challenging and the subsets found do not always guarantee the best results. However, the extracted solutions always allow a recognition rate higher than 95%, demonstrating the effectiveness of this trade-off between robustness and computational time.

4 Conclusion

An automatic technique for finding optimized marker layouts for marker-based facial motion capture is proposed in this paper. Specifically, by using 124 motion captures of 15 different subjects, each one containing the 3D position of 112 markers (109 markers fixed on the facial surface + 3 pasted on a rigid structure attached on the maxilla and used only as a reliable reference), the algorithm identifies the optimal facial marker layouts selecting the subset of measured features (i.e. distances among the 109 facial markers) that best allows for automatic recognition of the facial movements performed. To accomplish this task of "automatic recognition", a KNN classification technique, preceded by the application of a K-means clustering algorithm, is applied on a different subset of features, containing the distances among each marker and its neighbours. The subsets that best allows for the classification algorithm to automatically recognise the types of movement performed are chosen as the bests, and the marker layouts are extracted from them. Various validations and testing phases have demonstrated the accuracy, robustness and usefulness of the custom approach.

The layouts extracted can be directly used for facial motion acquisitions for guiding the marker application on the facial surface of the patients. Having standardized and optimal marker layouts was a long-standing problem remaining to be resolved in marker-based facial motion capture.

In the future, a deep look at the problem should be taken, in order to overcome the above limitations and improve the soundness and accuracy of automated extraction of marker layouts. For example, the training data may be enhanced by the introduction of others types of movements.

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Conflict of Interest Statement

All authors have approved the manuscript, agree with its submission to the journal, and certify that they have NO affiliations with or involvement in any organization or entity with any financial interest, or non-financial interest in the subject matter or materials discussed in this manuscript.

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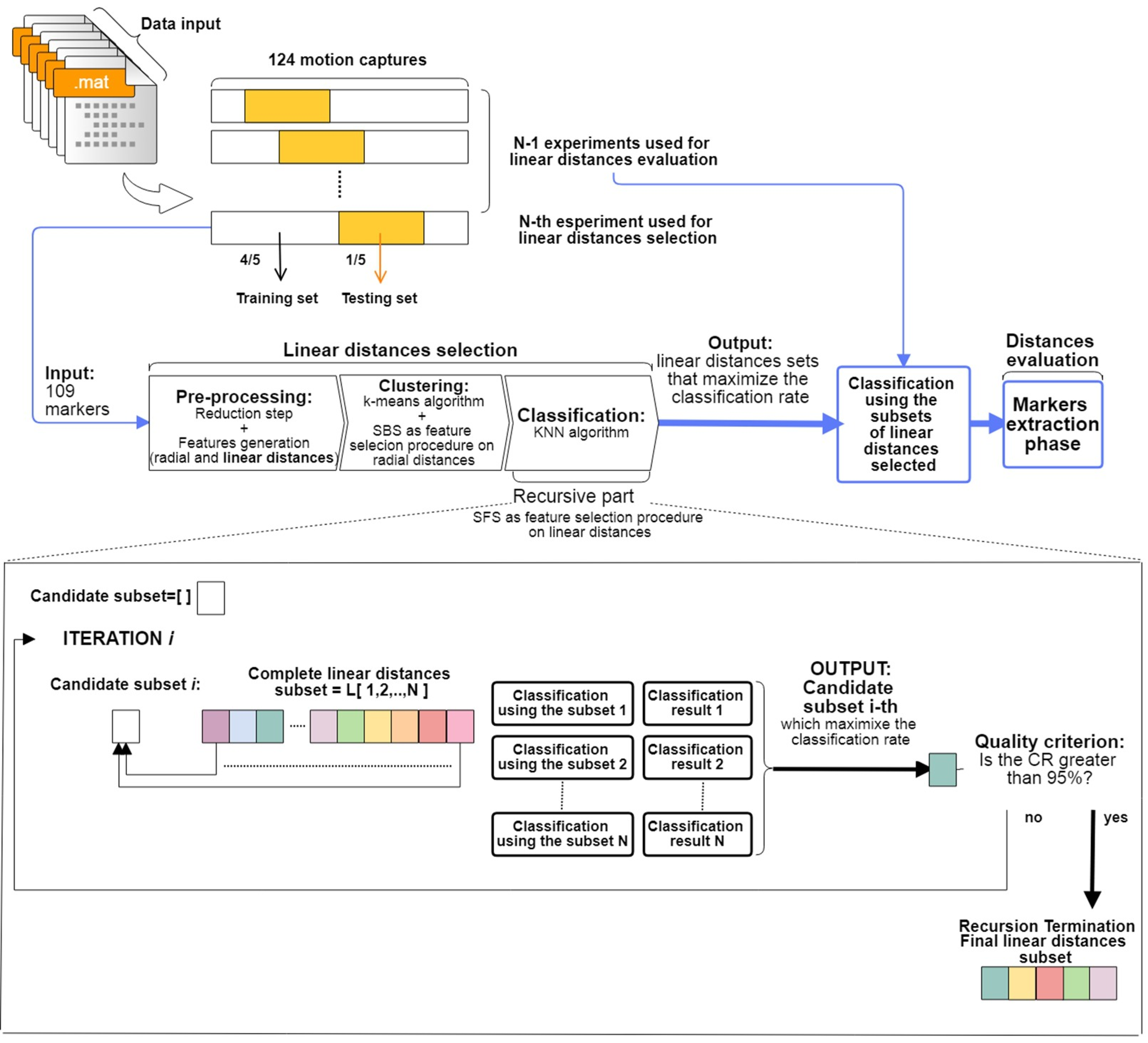
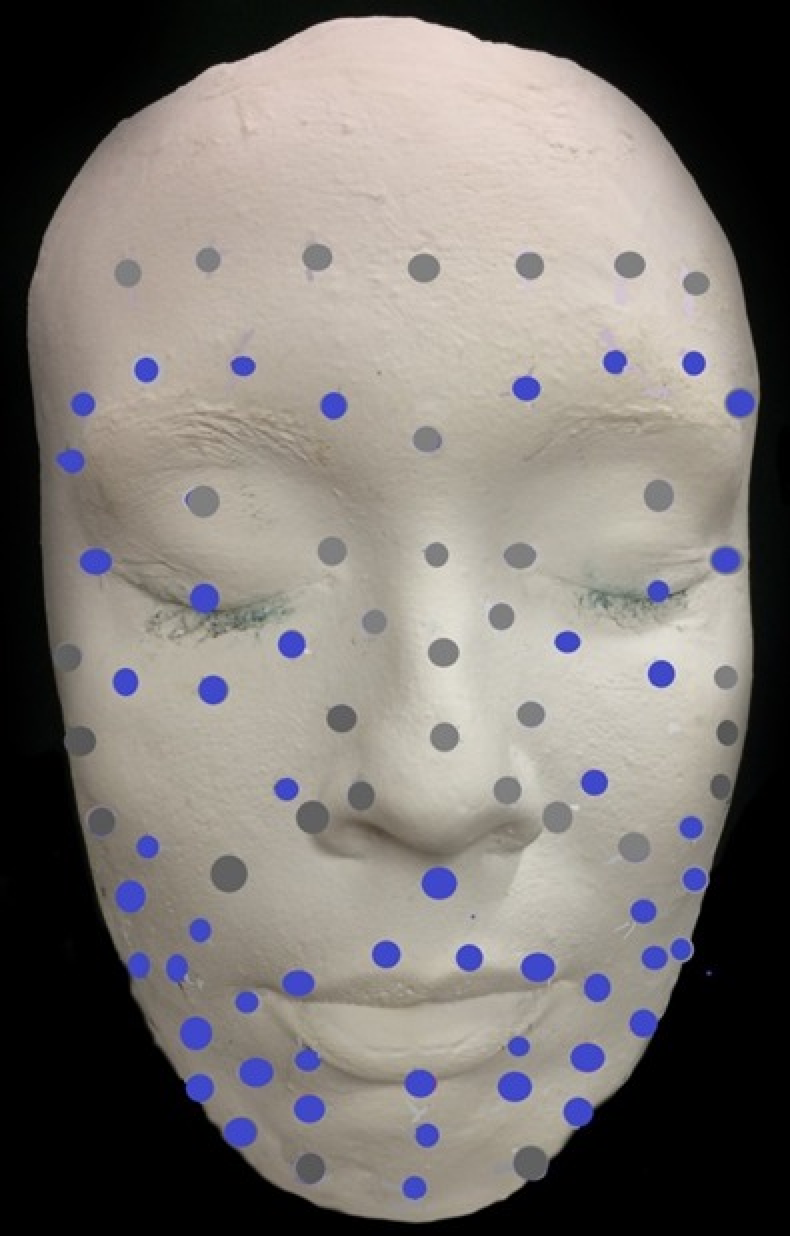
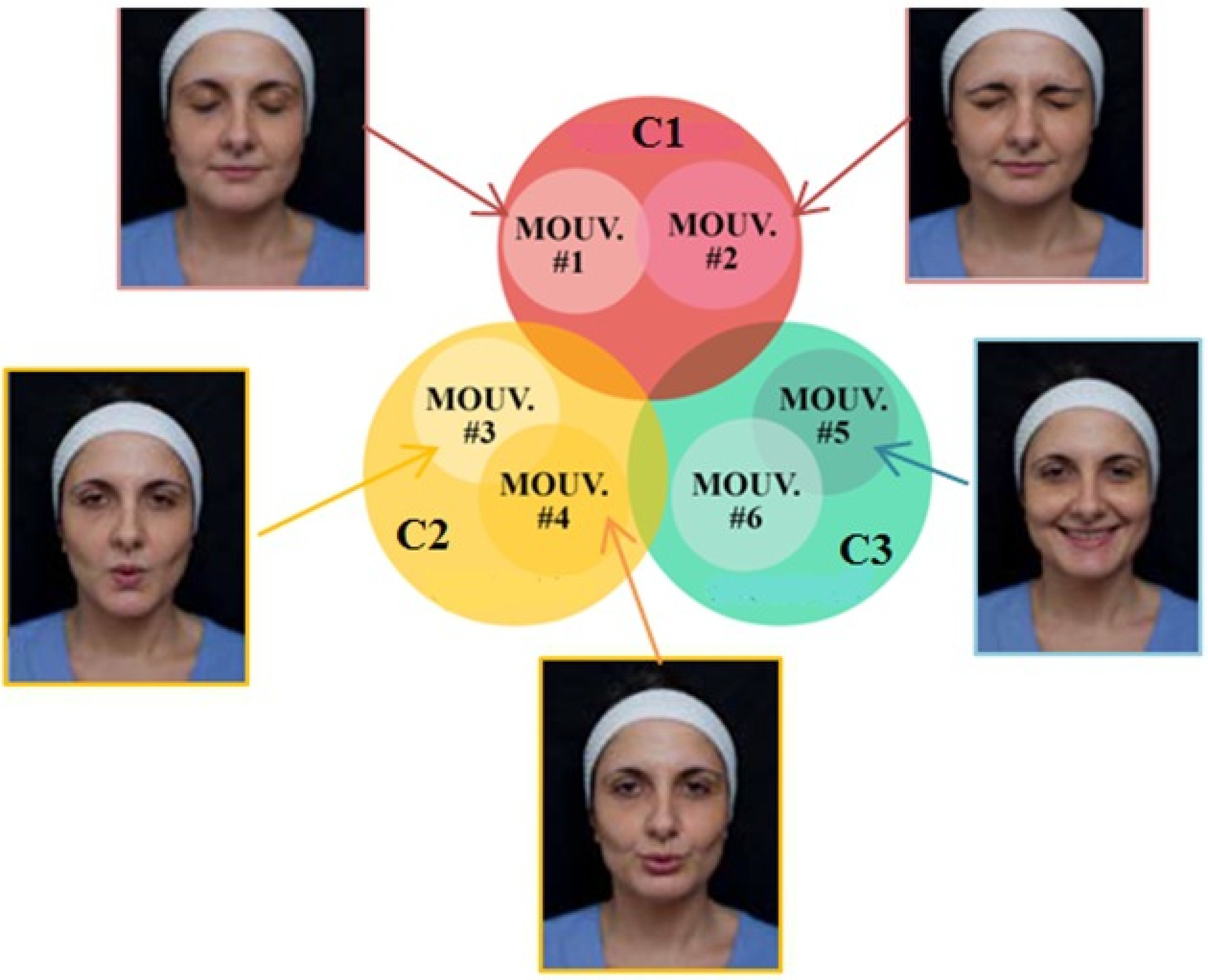
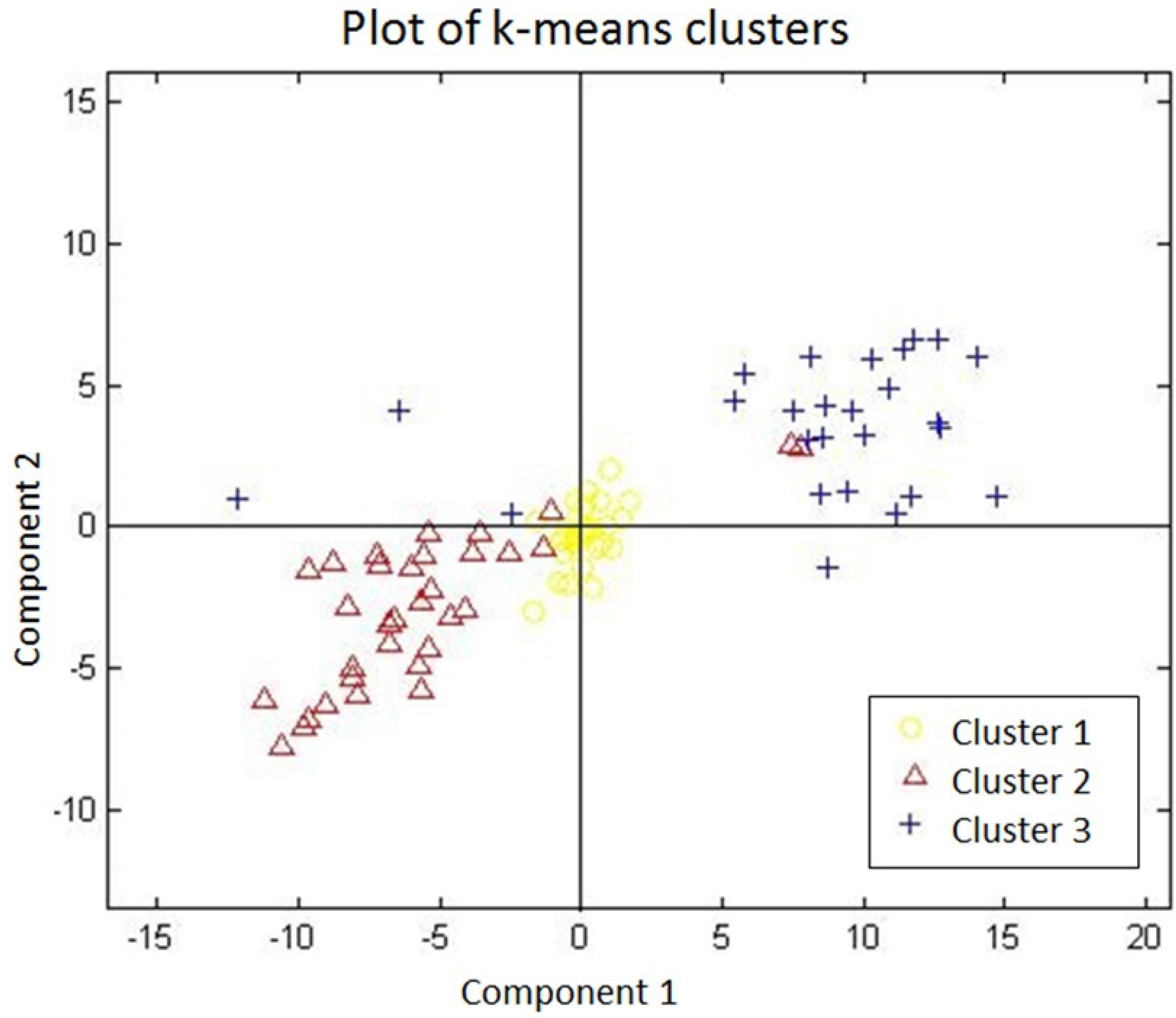


Data input
.mat
124 motion captures
N-1 experiments used for linear distances evaluation
N-th esperiment used for linear distances selection
4/5
1/5
Training set
Testing set
Linear distances selection
Input: 109 markers
Pre-processing: Reduction step + Features generation (radial and linear distances)
Clustering: k-means algorithm + SBS as feature selecion procedure on radial distances
Classification: KNN algorithm
Output: linear distances sets that maximize the classification rate
Classification using the subsets of linear distances selected
Distances evaluation
Markers extraction phase
Recursive part
SFS as feature selection procedure on linear distances
Candidate subset=[ ]
ITERATION i
Candidate subset i:
Complete linear distances subset = L[1,2,..,N]
Classification using the subset 1
Classification result 1
Classification using the subset 2
Classification result 2
Classification using the subset N
Classification result N
OUTPUT: Candidate subset i-th
which maximixe the classification rate
Quality criterion: Is the CR greater than 95%?
no
yes
Recursion Termination Final linear distances subset


Max
Min




C1
MOUV. #1
MOUV. #2
MOUV. #3
MOUV. #4
C2
MOUV. #5
MOUV. #6
C3



Plot of k-means clusters
Component 1
Component 2
Cluster 1
Cluster 2
Cluster 3
-15
-10
-5
0
5
10
15
20