Physical Activity Set Selection for Emotional State Harmonization Based on Facial Micro-Expression Analysis

Anna Chernenko [1], Maria Ashapkina [1], Victoria Sablina [1] and Alexey Alpatov [1]

[1] *Ryazan State Radio Engineering University named after V.F. Utkin, Gagarina st., 59/1, Ryazan, 390005, Russia*

Abstract

A new approach to harmonize a human emotional state is proposed. It is based on timely revealing and working through hidden negative emotions. The main ideas proving the possibility to implement this approach are described. The experimental investigation results for selected methods of revealing hidden negative emotions and working them through are represented. The video sequences reproducing emotions are used as input data. The ultimate research aim is the software system construction for the human emotional state harmonization. The effect of using such a system will be maintaining the health and increasing the quality of life of the modern human. The basic functions of this system are highlighted. The problem of repressing emotions and its possible negative consequences for the health are considered. The possibility of revealing repressed emotions from facial micro-expressions is justified. The main stages of the micro-facial movement detection by hybrid methods are considered in details. Each stage results are illustrated using the software pipeline developed in the previous research. It is proposed to work through revealed negative emotions by executing the individually selected physical activity set. The problem of the execution accuracy control of these exercises when working without assistance is considered. The health-improving exercise model is represented. The possibility of recording the motion trajectory using a smartphone software solution is shown. The method of the motion execution accuracy estimation on the basis of dynamic time warping is described. The development and implementation prospects of the proposed approach based on a smartphone software solution are justified.

Keywords

Micro-expression analysis, emotional state, physical activity, hybrid methods, rehabilitation, exercise therapy, performance accuracy, distance metrics, dynamic time warping.

1. Introduction

Improvements in the quality of life of the modern human are impossible without the physical and emotional health maintenance. A high level of stress in physiological and psychological systems carries a risk of difficulties in social interactions with friends, relatives and colleagues. The problems of decision making appropriate to the current situation arise. Often a negative psycho-emotional state is followed by a sleep disorder and an eating behavior deviation [1]. The long-term exposure of negative emotions could cause a nervous breakdown. In such a case the surrounding world perception adequacy is destroying. The transition to the psychosomatic illness could not be ruled out.

There are a fair number of available devices from balances and blood pressure gauges to physical activity trackers for the regular general physical health monitoring. However, the psycho-emotional state is often left without the control. It is related to the lack of available technical tools. It is also evident that the control of such states in itself should not be the ultimate work goal of the engineering system. It is important to not only monitor the repressed emotions but to suggest to a person the methods of relieving the negative emotional influences. It is known that the physical activity structured in the form of sets of exercises can normalize the human psychical activity [2]. It could cut off the symptoms of the negative emotional state and increase the psycho-emotional stability level.

GraphiCon 2022: 32nd International Conference on Computer Graphics and Vision, September 19-22, 2022,
Ryazan State Radio Engineering University named after V.F. Utkin, Ryazan, Russia
EMAIL: anuta201294@yandex.ru (A. Chernenko); mashaashapkina@gmail.com (M. Ashapkina); sablina.v.a@evm.rsreu.ru (V. Sablina); alpatov-alexey@yandex.ru (A. Alpatov)
ORCID: 0000-0003-4323-1266 (A. Chernenko); 0000-0002-7757-1501 (M. Ashapkina); 0000-0001-9248-9904 (V. Sablina); 0000-0001-9694-6818 (A. Alpatov)

Thereupon it appears urgent to create an engineering system which would combine the following basic functions:

- the possibility to use in the "always at hand" mode without the need of the constant stay in the medical institution;
- the function of the emotional state recognition function at the moment and its subsequent classification as positive or negative;
- the function of the intensity and duration determination of being of the person in one of the emotional state classes;
- the function of the recommendation of the physical activity set accessible to execution without assistance;
- the function of the accuracy and regularity control of the execution of the physical exercises;
- the function of the feedback about the emotional state at the moment and about the execution of the physical execution.

The proposed in this work solution is aimed to create the human emotional state maintenance and harmonization system. This system is based on registration of parameters of human facial micro-expressions and the execution accuracy of health-improving exercises using the modern smartphone video camera.

It is necessary to solve two main tasks using the video stream data to implement the basis functional of the proposed system:

- developing the technology of the automatic human facial micro-expression analysis;
- developing the method of the execution accuracy estimation of physical exercises.

Further the proposed solutions to these tasks are considered in details.

2. The problem of repressed emotions influence to the human health

Repressing emotions on a regular basis could create a negative impact on the human emotional state [3]. Being in a disharmonized emotional state for a long time in turn could influence destructively to the human organism. It is required to reveal in the proper time which emotions a person represses mostly to return to the balanced emotional state. Usually, the following emotions are considered: happiness, sadness, surprise, fear, anger, disgust, and contempt [4]. Positive emotions don't provide the destructive influence. Conscious suppression of emotions is controlled by a person. That's why their influence could be leveled out by this person himself or herself. Therefore, the most problem is the case of unconscious repression of negative emotions [5]. In this case the person could consult a psychologist to reveal the repressed emotions. However, in such a way the process will take place "by hand".

The modern technologies make it possible to perform this process automatically using computer vision methods. But the required mathematical methods and algorithms to do this are only being investigated and developing at present time [6]. The promising results obtained in our previous research works [7-10] are basic to the proposed technique of the physical activity set selection for emotional state harmonization.

In the present work we propose to use for revealing hidden emotions the human facial micro-expression analysis methods [11]. The scientific base for this approach is psychological investigations of many years [12]. These investigations show that true human emotions appear on the face in the form of the micro-expressions. They arise as the result of the human attempts to hide his or her emotions consciously or unconsciously. In such cases the micro-expressions appear on the face and last less than a half of a second. A micro-expression corresponds to the manifestation of some known emotion [7].

It would be convenient to perform revealing the repressed emotions by the contactless method using a high-speed camera. A camera of a modern smartphone can capture up to 240 frames per second or even more for some models. Further we demonstrate the feasibility in principle of performing this process on the basis of the hybrid methods of human facial micro-expression analysis. We represent the general description of an implemented version of the developed software pipeline [8] for carrying out experimental investigations of mathematical methods and algorithms.

3. Revealing the repressed emotions from facial micro-expressions

The micro-expression corresponded to a specific emotion can be recognized on the basis of the micro-facial movement combination. This correspondence is described in the Facial Action Coding System (FACS) [13]. Therefore, the main problem of the automatic recognition of the repressed emotions consists in the correct detection of the presence of the micro-facial movements. In our previous research work we proposed the micro-facial movement detection pipeline [8]. This pipeline is implemented using the MATLAB® and Python® programming languages. The input data for experimental investigations of the developed software pipeline is the Spontaneous Actions and Micro-Movements (SAMM) dataset recorded at the speed of 200 frames per second [14]. It consists of the image sequences of the faces with the spontaneous micro-expressions. The set contains 159 spontaneous facial micro-expressions image sequences of people belonging to different gender, race, and nationality groups. This set is prepared by the research group from the Manchester Metropolitan University. The processing of input image sequences $\{I_k\}, k=\overline{1,N}$ in the pipeline is performed by the hybrid methods. Figure 1 shows the main stages of the developed micro-facial movement detection pipeline. The utilized approaches are indicated below for each stage. It is possible to select different specific methods or algorithms which give us different combinations for the software pipeline implementation. Further the most efficient combination from the experimental results is briefly described. As the criterion to estimate the efficiency of a certain version we used the percent of correct detections in the Boolean vector of presence of the micro-facial movements $\mathbf{m}$ on all the selected image sequences from the SAMM dataset. We used in the experiments about one-third fraction of this dataset.

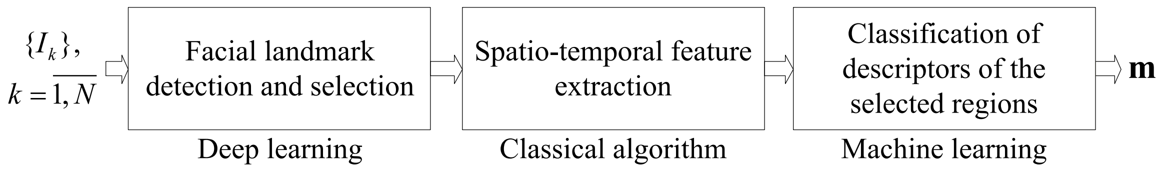
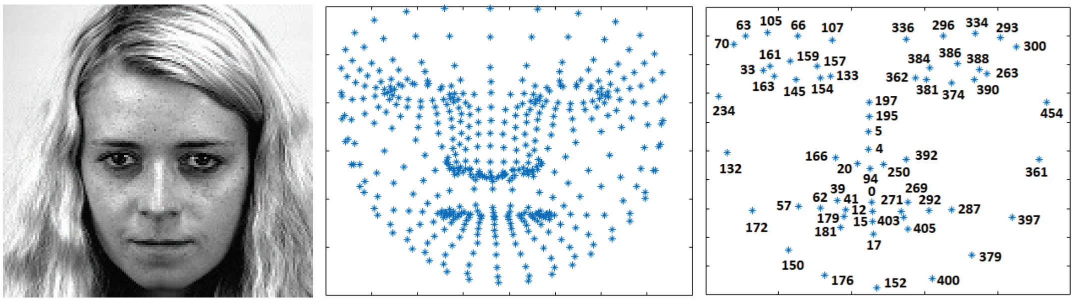


Figure 1: The main stages of the facial micro-facial movement detection by the hybrid methods

3.1. Facial landmark detection and selection

Deep learning methods can be used only at the first stage because for the lack at the present time of the datasets of micro-movements with the sufficient for these methods quantity of images. But this is possible for the facial landmark detection, since the neural network preliminary trained on the facial images without micro-expressions is used [9]. The landmark detection is performed using the MediaPipe framework [15] on the basis of the TensorFlow library [16]. The TensorFlow library includes the implementation of the preliminary trained model for the facial landmark detection. It could be used to predict 468 facial landmarks of the MediaPipe Face Mesh solution using transfer learning methods. The layout to select the 62 landmarks in the regions of the possible micro-facial movements from these 468 landmarks is proposed.

Figure 2 represents an example of the stage results of the facial landmark detection and selection in the indicated way. An image from the SAMM dataset is presented in Figure 2, a. The girl in the image in Figure 2, a is feeling the hidden aggression as she is screwing her eyelids. However, it is hardly visible to an unaided eye. Figure 2, b shows 468 detected MediaPipe Face Mesh landmarks for the image in Figure 2, a. Figure 2, c shows 62 selected landmarks which are fed to the next stage of the pipeline. The numbers of the landmarks correspond to the numbering in the MediaPipe Face Mesh. We select only the landmarks which could participate in the micro-facial movements. Moreover, the thinning of the landmarks is performed to reduce the amount of computation. This is possible because 468 detected MediaPipe Face Mesh landmarks are too thickly located for the considered task.



a b c

Figure 2: Facial landmark detection and selection: a – an image from the SAMM dataset; b – 468 detected MediaPipe Face Mesh landmarks; c – 62 selected landmarks in the regions of the possible micro-facial movements

3.2. Spatio-temporal feature extraction

The 3D block construction algorithm to select the regions around the facial landmarks is proposed [8]. In so doing, the image sequence $\{I_k\}, k=\overline{1,N}$ is considered in the three dimensions: two of them, x and y, are spatial and one of them, t, is temporal. Further we need to calculate the feature descriptor vector for each block. At this stage the Local Binary Patterns from Three Orthogonal Planes (LBP-TOP) [17-19] descriptor algorithm is used. This is a classical mathematical algorithm without using neural networks. This algorithm has a number of adjustable parameters. The satisfactory combinations of these parameters are found in the course of experimental investigations. These combinations provide the greatest percent of the correctly detected micro-facial movements for the considered samples of image sequences. One of the most successful combinations of the LBP-TOP algorithm parameters is represented in Table 1. The parameters most influencing on the result are indicated. Therefore these parameters are selected for adjusting. They are set to the values from Table 1 in the ultimate version of the developed software pipeline. The neighbor points placement trajectory definition coefficients show that it is preferable to select in the spatio-temporal planes the trajectory in the form of the ellipse and not the circle.

Table 1
Found parameters of the LBP-TOP algorithm for calculating block feature descriptors

Block division value for each axis	Block overlapping value for each axis	Neighbor points placement trajectory definition coefficient in the plane *Oxt*	Neighbor points placement trajectory definition coefficient in the plane *Oyt*
5	0,1	0,1	0,3

3.3. Classification of descriptors of the selected regions

At the stage of classification of feature descriptors of the selected regions it is possible to use the machine learning methods [20]. However, the deep learning methods are not suitable because there is not enough data for learning. The known neural network architecture is selected in the course of the carried out experiments to implement this pipeline stage. This is the Multilayer Perceptron (MLP). The use of the MLP makes it possible to reach the overall result of 98 % of the correct detection of the micro-facial movements for the utilized part of the SAMM dataset.

4. The problem of the accuracy control of the execution of the exercises

After identifying suppressed emotions by facial micro-expressions, an individually selected set of physical exercises can be prescribed to harmonize the emotional state [21]. A set of exercises is recommended to be performed at home regularly for a specified period of time. The impact on the emotional state can be assessed by again analyzing the repressed emotions by facial micro-expressions in the same or similar conditions. The effectiveness of the described approach will depend on the correctness of the selected set of physical exercises. This raises the problem of automatic control of the correctness of its implementation.

4.1. The problem of monitoring the correctness of the exercises

Self-training with a set of corrective exercises requires strict observance of the exercise technique. However, most people do not have special knowledge on the exercise technique, often the movements are not performed regularly and not in full. For this reason, the effectiveness of exercise is greatly reduced. Obviously, at home, a person does not have the opportunity to competently control the correctness of the exercises and their positive impact on the psycho-emotional state [22].

Objective data on the correctness of the exercises, combined with the control of hidden emotions, will allow us to build an optimal methodology for conducting classes that correct the psycho-emotional state.

In general, the presence of these problems requires the search for technological solutions and the introduction of available methods for objective control of the process of the musculoskeletal system during exercise. This problem can be solved with the help of remote tracking based on video control using a smartphone video camera.

The result of video monitoring of the exercise should be a trajectory of a motor act that describes a change in the position or orientation of the joint subjected to the load in space in time. The trajectory correctness evaluation is based on the use of special quantitative metrics.

4.2. Health-improving exercise model

The musculoskeletal system is a complex mechanical system with a high degree of freedom. The kinematic model of human joints consists of movable joints and bone links, and such a system can generate many trajectories determined by the task of a particular motor act.

The essence of any physical exercise is to create a load on the muscles, by forming a clear sequence of acts of flexion, extension. Physical exercise is cyclic, the limb always returns to its original position, and each exercise has a maximum position that characterizes the maximum deformation in the joint.

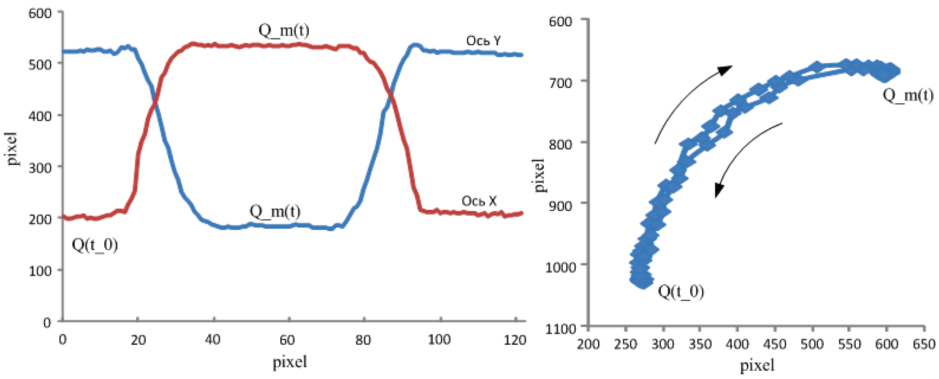
Usually the health-improving exercise protocol includes a small number of simple movements that almost anyone can perform without special sports training.

Consider the formation of movement trajectories of one of the popular breathing exercises. We represent the joint model as a kinematic pair: ankle-pelvis-shoulder-elbow-wrist. In this model, the pelvis and ankle are a fixed support with a ball joint, the target movement is initiated in the shoulder-knee-wrist link, and the shoulder-elbow-wrist link forms a single link. After the limit position of this link in space, movement occurs in the opposite direction to the starting position.

The protocol of the exercise excludes additional movements and imposes a restriction on the movement of the knee only in the $X0Y$ plane (sagittal plane), neglecting the frontal and horizontal movements. Let there be a reference trajectory at the point of the carpal joint (Figure 3) in the form:

$$Q(t) = \{Q_X(t), Q_Y(t)\} \tag{1}$$

where $Q(t\_0)$ is the starting position, $Q\_m(t)$ is the most distant point of the trajectory from the starting position, it is the limit position, $t = [0, T]$ is the time of one iteration of the exercise in seconds.



a b

Figure 3: An example of the formation of an exercise trajectory along the *X* and *Y* axes for the exercise "Breathing exercise in a lying position": a – the time dependence; b – the spatial trajectory

So, let there be a set of exercises in the form of a set *F*, given as

$$F = \{Q_i, T_i\}, i = [\overline{1, K}] \quad (2)$$

where Q_i is the reference trajectory of the *i*-th rehabilitation exercise, T_i is the duration of the *i*-th rehabilitation exercise, *K* is the number of rehabilitation exercises.

The actual performance of the exercises leads to the formation of a set *F*` with the corresponding trajectories and duration. Hence, the criterion for the correctness of the exercise is the fulfillment of the condition $F` \rightarrow F$.

Thus, the task of monitoring the correctness of the exercise consists of the following subtasks:

- obtaining the trajectory of movement at the control point of the movable link, relative to the link of the fixed support;
- estimation of the measure of similarity of trajectories *Q*` at the control point with its reference image *Q*.

The modern approach to the problem of controlling motor activity and determining the position of the body in space is based on a motion capture system based on video recording data [23].

4.3. Registration of the motion path

Within the framework of this work, the task of obtaining the trajectory of the control point was solved based on the use of the MediaPipe framework [15]. MediaPipe Pose is a high-precision body pose tracking machine learning solution that derives 33 3D landmarks and a full-body background segmentation mask from video frames.

The advantage of this framework is the ability to work in real time on most modern smartphones based on Android and iOS, as well as PCs using Python.

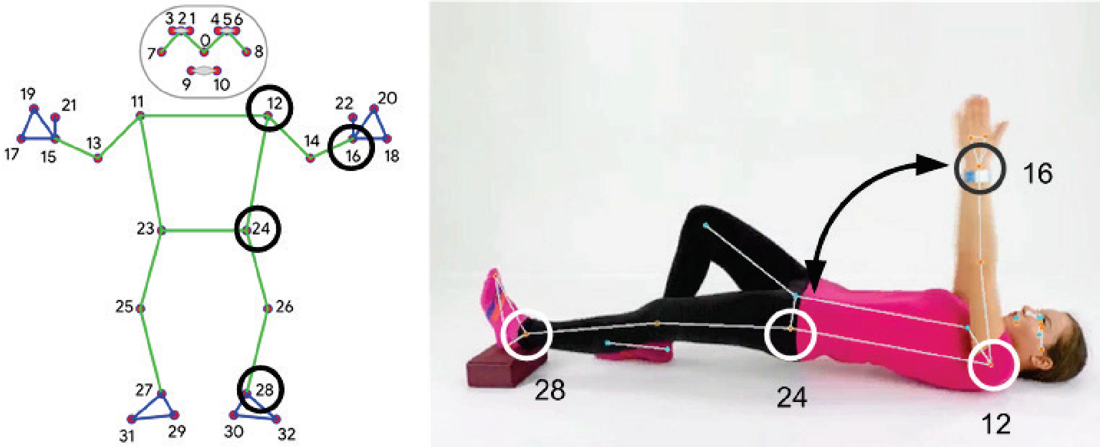
To prototype the registration system, a Python based project was developed, for this, preparations have been made.

First, a video was made of basic exercises recommended to reduce emotional stress. When shooting, the need to have a head in the frame was taken into account, which is one of the key points for the operation of a human detector. The shooting is mounted as one cycle of the exercise.

Second, for each exercise, a model is built in terms of the landmark model in MediaPipe Pose predicts the location of 33 pose landmarks. Support points, points of the target trajectory are selected. For example, for a breathing exercise in a lying position, it would look like this:

- ankle (static);
- pelvis (small amplitude dynamics);
- shoulder (static);
- wrist (basic movement).

For this example, the trajectory of movement is formed by tracking the wrist relative to the ankle-shoulder line. A similar operation was performed for the remaining 13 exercises. The description of the set of exercises in the form of a list of key points is structured as a json file. The scheme of the exercise and an example of tracking is shown in Figure 4.



a b

Figure 4: MediaPipe Pose predicts the location of pose landmarks for a breathing exercise in a lying position: a - BlazePose 33 keypoint topology, b - an example of selecting key points for a breathing exercise

Before performing the exercise, a voice command is given to take a starting position. The position of the control points relative to each other is fixed and checked according to the protocol of the exercise. If fluctuations in the movement of the control point (wrist) or an incorrect location of the control points are detected, then the appropriate commands are issued: incorrect starting position or please do not move [24].

4.4. The method of the motion execution accuracy estimation on the basis of discrete wavelet transform

One of the methods to combine time scales is the linear alignment of pairs of points of the real trajectory and the standard on the basis of the minimum distance. There is a group of algorithms based on finding the optimal path for such an alignment, based on the dynamic programming method. In this paper, it is proposed to use the method of dynamic time scale transformation DTW (dynamic time warping).

The essence of the method is as follows. Let there be two discrete realizations of the trajectory $Q = (q_1, q_2, \cdots q_i, \cdots q_n)$, $Q' = (q_1^{'}, q_2^{'}, \cdots q_j^{'}, \cdots q_m^{'})$, where n and m are the number of readings. To align the two implementations, we calculate an $n \times m$ matrix of mutual distances for all variants of the q_i and $q_j^{'}$, pairs, where each i-th and j-th element will contain the value of the Euclidean distance (this is the usual variant, in the general case, the metric can be any) of the form $d_{ij} = (q_i - q_j^{'})^2$. Further, according to the distance matrix, the deformation matrix *D(i,j)* is calculated in the vicinity of the current element of the matrix d_{ij} according to the rule:

$$D(i,j) = \begin{cases} 0 & i = 0, j = 0; \\ \infty & \begin{matrix} i = 0, j > 0; \\ i > 0, j = 0; \end{matrix} \\ d_{ij} + min \begin{cases} D(i-1, j-1) \\ D(i-1, j) \\ D(i, j-1) \end{cases} & i, j \geq 1 \end{cases} \quad (3)$$

where $i = [\overline{1,n}]$, j= $[\overline{1,m}]$.

To determine the best alignment between the elements of the trajectories Q and Q', you need to find a deformation path W that will minimize the total distance between them. Then

$$W = (w_1, w_2, \cdots w_k) \quad (4)$$

where $max(n,m) \leq k \leq n + m + 1$, $k = [\overline{1,K}]$, K is the path length, i.e. number of matrix elements $D(i,j)$, on which the path W passed.

The elements of the path W are defined in matrix coordinates $D(i,j)$ as $w_k = (i,j)_k$. To prevent incorrect path construction, strict restrictions are imposed on it:

- boundary conditions for passing through the matrix elements from position $D(n,m)$ to $D(0,0)$, i.e. in diagonally opposite corner cells of the matrix. This ensures that the path passes through all points of the trajectories.
- continuity of indices i and j, i.e. in one step, they can only increase by 1 together or individually, which prevents indexing breaks;
- monotonicity of the increment of indexes i and j, guarantees the impossibility of returning to the traversed element [25].

The scheme of the trajectory estimation algorithm based on this method is shown in Figure 5.

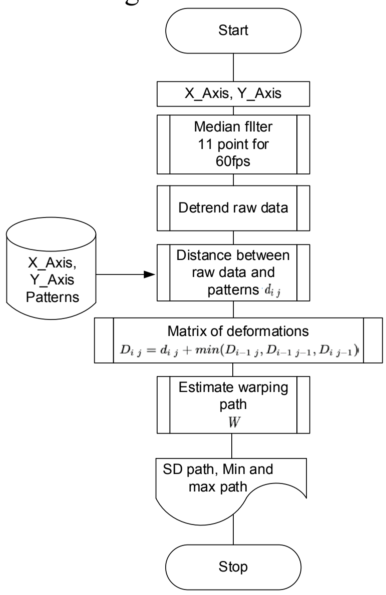


Figure 5: Scheme of the DTW algorithm for assessing the correctness of the exercises

The final metric DTW, the distance, is calculated as the minimum of all possible minimum paths, reduced to the maximum path length $n + m$:

$$DTW(Q, Q') = min\left\{\frac{\sum_{k=1}^{K} w_k}{n+m}\right\}. \quad (5)$$

For two identical data sets there will be a matrix diagonal. Path deviation measure from diagonal is indirect indication of rotation angles patterns incongruity. We describe the example of accounting result for exercise of tibia lift in Figure 6.

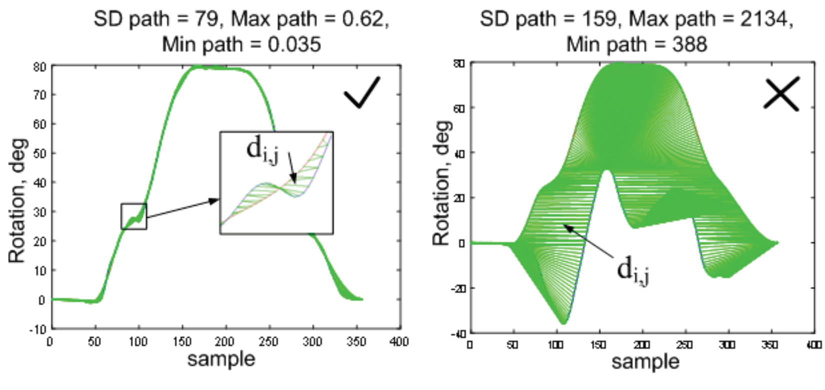


Figure 6: Calculated data of performing accuracy according to DTW algorithm: a – correct performing; b – incorrect performing

In Figure 6 we show minimum distances of points of basic and model signals with the pecked line. Figure 6, a demonstrates the results of correct exercise performing, Figure 6, b demonstrates incorrect performing, that is the exercise was performed along the incorrect path.

5. Conclusion

The paper proposes a new approach for human emotional state harmonization; however, the represented ideas and concepts are required to be developed in the further investigations. The ultimate goal of the research in the considered direction is to prevent psychosomatic diseases. The proposed approach is based on the early detection of accumulated hidden negative emotions in a person. Methods have been explored both for identifying and for working out such emotions. The conducted experiments confirm the possibility of using the chosen methods to solve the problems under consideration. To identify hidden negative emotions, it is proposed to use methods for analyzing micro-expressions of a person's face. The software pipeline developed in previous works makes it possible to detect micro-facial movements based on hybrid methods. The presented pipeline in the future can be used to reveal hidden negative emotions. To work out such emotions, it is proposed to use individually selected sets of physical exercises. A method for monitoring the correctness of the exercises has been developed. All the proposed methods are united by a uniform implementation, which will allow us to develop a unified software system in the future. A high-speed camera is used as a sensor to obtain information. The software implementation relies on the functions of the MediaPipe framework. This will allow in the future implementing the presented ideas in the form of a mobile application for a regular smartphone. Nevertheless, the proposed approach requires further theoretical and experimental study and justification for implementation on a scientific basis.

6. References

[1] Li Zhang, Youling Bai, Xiaobing Cui, Gege Cao, Dan Li, and Huazhan Yin, Negative Emotions and Brain: Negative Emotions Mediates the Association Between Structural and Functional Variations in Emotional-Related Brain Regions and Sleep Quality, Sleep Medicine, Volume 94, 2022, pp. 8-16. doi: 10.1016/j.sleep.2022.03.023.

[2] Candice L. Hogan, Lahnna I. Catalino, Jutta Mata, and Barbara L. Fredrickson, Beyond Emotional Benefits: Physical Activity and Sedentary Behaviour Affect Psychosocial Resources Through Emotions, Psychology and Health, Volume 30, Issue 3, 2015, pp. 354-369. doi: 10.1080/08870446.2014.973410.

[3] Jainish Patel and Prittesh Patel, Consequences of Repression of Emotion: Physical Health, Mental Health and General Well Being, International Journal of Psychotherapy Practice and Research, 1 (3), 2019, pp. 16-21. doi: 10.14302/issn.2574-612X.ijpr-18-2564.

[4] Paul Ekman Group®, Universal Emotions, [accessed 2022 August 19]. URL: https://www.paulekman.com/universal-emotions/ .

[5] Simon Boag, Repression, Suppression, and Conscious Awareness, Psychoanalytic Psychology, 27 (2), 2010, pp. 164-181. doi: 10.1037/a0019416 .

[6] Yee-Hui Oh, John See, Anh Cat Le Ngo, Raphael C.-W. Phan, and Vishnu M. Baskaran, A Survey of Automatic Facial Micro-Expression Analysis: Databases, Methods, and Challenges, Frontiers in Psychology Journal, Volume 9, Article 1128, 2018, 21 p. doi: 10.3389/fpsyg.2018.01128.

[7] Anna D. Sergeeva, Alexander V. Savin, Victoria A. Sablina, and Olga V. Melnik, Emotion Recognition from Micro-Expressions: Search for the Face and Eyes, 8th Mediterranean Conference on Embedded Computing (MECO) Proceedings. Budva, Montenegro, 2019. Pp. 632-635. doi: 10.1109/MECO.2019.8760029.

[8] Giovanni Burresi and Victoria A. Sablina, Micro-Facial Movement Detection Using LBP-TOP Descriptors for Landmark Based Regions, 10th Mediterranean Conference on Embedded Computing (MECO) Proceedings. Budva, Montenegro, 2021. Pp. 401-404. doi: 10.1109/MECO52532.2021.9460142.

[9] Alexander V. Savin, Victoria A. Sablina, and Michael B. Nikiforov, Comparison of Facial Landmark Detection Methods for Micro-Expressions Analysis, 10th Mediterranean Conference on Embedded Computing (MECO) Proceedings. Budva, Montenegro, 2021. Pp. 336-339. doi: 10.1109/MECO52532.2021.9460191.

[10] Anna D. Sergeeva and Victoria A. Sablina, Eye Landmarks Detection Technology for Facial Micro-Expressions Analysis, 9th Mediterranean Conference on Embedded Computing (MECO) Proceedings. Budva, Montenegro, 2020. Pp. 448-451. doi: 10.1109/MECO49872.2020.9134338.
[11] Walied Merghani, Adrian K. Davison, and Moi Hoon Yap, A Review on Facial Micro-Expressions Analysis: Datasets, Features and Metrics, Preprint submitted to IEEE Transactions, Computer Vision and Pattern Recognition, 2018, 19 p. [accessed 2022 May 12]. URL: https://arxiv.org/abs/1805.02397. doi: 10.48550/arXiv.1805.02397.
[12] Paul Ekman, Emotion in the Human Face, 2nd Edition, Malor Books, 2013, 456 p.
[13] Adrian K. Davison, Walied Merghani, and Moi Hoon Yap, Objective Classes for Micro-Facial Expression Recognition, Journal of Imaging, 4 (10), 119. 2018, 13 p. doi: 10.3390/jimaging4100119.
[14] Adrian K. Davison, Cliff Lansley, Nicholas Costen, Kevin Tan, and Moi Hoon Yap, SAMM: A Spontaneous Micro-Facial Movement Dataset, in IEEE Transactions on Affective Computing, Volume 9, No. 1, 2018, pp. 116-129. doi: 10.1109/TAFFC.2016.2573832.
[15] MediaPipe on GitHub, [accessed 2022 May 12]. URL: https://google.github.io/mediapipe/ .
[16] Yury Kartynnik, Artsiom Ablavatski, Ivan Grishchenko, and Matthias Grundmann, "Real-time Facial Surface Geometry from Monocular Video on Mobile GPUs," CVPR Workshop on Computer Vision for Augmented and Virtual Reality 2019, IEEE, Long Beach, CA, 4 p. [accessed 2022 May 12]. URL: https://arxiv.org/abs/1907.06724. doi: 10.48550/arXiv.1907.06724.
[17] Adrian K. Davison, Moi Hoon Yap, Nicholas Costen, Kevin Tan, Cliff Lansley, and Daniel Leightley, Micro-Facial Movements: An Investigation on Spatio-Temporal Descriptors, In ECCV 2014, Lecture Notes in Computer Science, vol. 8926, Springer, Cham., 2015, pp. 111-123. doi: 10.1007/978-3-319-16181-5_8.
[18] Shiyu Zhang, Bailan Feng, Zhineng Chen, and Xiangsheng Huang, Micro-Expression Recognition by Aggregating Local Spatio-Temporal Patterns, In MMM 2017, Lecture Notes in Computer Science, vol. 10132, Springer, Cham., 2017, pp. 638-648. doi: 10.1007/978-3-319-51811-4_52.
[19] Xiaopeng Hong, Yingyue Xu, and Guoying Zhao, LBP-TOP: A Tensor Unfolding Revisit, In ACCV 2016, Lecture Notes in Computer Science, vol. 10116, Springer, Cham., 2017, pp. 513-527. doi: 10.1007/978-3-319-54407-6_34.
[20] Iyanu Pelumi Adegun and Hima BinduVadapalli, Facial Micro-Expression Recognition: A Machine Learning Approach, Scientific African Journal, Volume 8, e00465, 2020, 14 p. doi: 10.1016/j.sciaf.2020.e00465.
[21] Zhengji Long, Guangyuan Liu, Zhangyan Xiao, and Pengfei Gao, Improvement of Emotional Response to Negative Stimulations With Moderate-Intensity Physical Exercise, Front. Psychol. 12:656598, 01 July 2021. doi: 10.3389/fpsyg.2021.656598.
[22] Maria S. Ashapkina, Alexey V. Alpatov, and Victoria A. Sablina, Online System for Involving Patients in Home-Base Rehabilitation Programs for the Knee Joint, 9th Mediterranean Conference on Embedded Computing (MECO) Proceedings. Budva, Montenegro, 2020. Pp. 730-733. doi: 10.1109/MECO49872.2020.9134070.
[23] Maria S. Ashapkina, Alexey V. Alpatov, Victoria A. Sablina, and Alexander A. Chekushin, Quantitative Parameters Developing for Estimation of Rehabilitation Exercising on The Basis of IMU Sensor Device, 7th Mediterranean Conference on Embedded Computing (MECO) Proceedings. Budva, Montenegro, 2018. Pp. 541-544. doi: 10.1109/MECO.2018.8405987.
[24] Maria S. Ashapkina, Alexey V. Alpatov, and Victoria A. Sablina, Smartphone-based Systems for Knee Joint Physical Rehabilitation, 9th Mediterranean Conference on Embedded Computing (MECO) Proceedings. Budva, Montenegro, 2020. Pp. 726-729. doi: 10.1109/MECO49872.2020.9134249.
[25] M.S. Ashapkina, A.V. Alpatov, V.A. Sablina, and A.V. Kolpakov, Metric for Exercise Recognition for Telemedicine Systems, 8th Mediterranean Conference on Embedded Computing (MECO) Proceedings. Budva, Montenegro, 2019. Pp. 668-671. doi: 10.1109/MECO.2019.8760024.