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Toward an Efficient Body Expression Recognition Based on the Synthesis of a Neutral Movement

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Figure 1: Our method recognizes the expression of a human 3D skeleton animation.

ABSTRACT

We present a novel framework for the recognition of body expressions using human postures. Proposed system is based on analyzing the spectral difference between an expressive and a neutral animation. Second problem that has been addressed in this paper is formalization of neutral animation. Formalization of neutral animation has not been tackled before and it can be very useful for the domain of synthesis of animation, recognition of expressions, etc. In this article, we proposed a cost function to synthesize a neutral motion from expressive motion. The cost function formalizes a neutral motion by computing the distance and by combining it with acceleration of each body joints during a motion. We have evaluated our approach on several databases with heterogeneous movements and body expressions. Our body expression recognition results exceeds state of the art on evaluated databases.

CCS CONCEPTS

- Computing methodologies → Activity recognition and understanding; Motion capture;

KEYWORDS

Computer Vision; Body Expression; Automatic Recognition; 3D Skeleton; Classification

ACM Reference Format:


1 INTRODUCTION

Many applications would benefit from the ability to understand human emotional state in order to provide more natural interaction, e.g. video games, video surveillance, human-computer interaction, artistic creation, etc. Emotion is a complex phenomena that is difficult to formalize. Expression of an emotion could be personal and subjective as two persons could perceive and interpret differently the same expression. Its perception changes from one culture to another [18]. Furthermore, human expresses emotional information through several channels, like facial expression, body movement and sound. Several studies from various domains have shown that body expressions are as powerful as those of the face to express emotion [17]. Whereas facial expression recognition was widely studied [7, 13, 15, 16], body expression recognition is more an emerging area. Early proposed methods for body movement analysis [14, 19] were limited to specific movements or expressions. Nevertheless,
with the growth and ease of accessibility of devices that track 3-
dimensional body like the Kinect [4, 22] or accelerometer [26] based
motion capture system, many applications will benefit from analysis
of body movements.

This paper presents a method to detect and classify expression
through a sequence of 3D skeleton-based poses. The challenge is
to have a system that recognizes the expression invariant to body
movement. For example, expression of happiness could be shown
while running, jumping, kicking, etc.

In the rest of the paper, depending on the case involved we use
the term “Body Expressions” to refer to emotion expressed by body
posture while term of style refers to the domain of synthesis of
animation. Style is an important component of character animation,
as that includes aesthetic, original, and emotional characteristics.
For instance, an old walking, a depressed kicking, a character with
a wooden leg, etc. are different way to express how a motion differs
from the neutral movement.

Inspired by style transfer in animation synthesis [33], we have
used the difference between an expressive and corresponding neu-
tral animation for classification. The difference efficiently makes
the purpose system independent of the movement. Computing this
residue requires a neutral motion. Since real applications capture
the whole movement including the expression, we proposed to
retrieve a neutral motion from an expressive motion. We compute
the residue in the frequency domain between the neutral motion
produced by our method and the input motion containing the ex-
pression. This residue is used by classifier in order to recognize the
body expression. We have evaluated our work on four databases
that contains heterogeneous movements and expressions.

The paper is organized as follows. Section 2 presents the state
of the art on emotion analysis. Section 3 details our method. In
Section 4 we present the results obtained on different databases.
We compared our method with state-of-the-art approaches. Finally,
Section 5 concludes the paper and presents future work.

2 RELATED WORK

In recent years, researchers have mainly focused on automatic facial
expression recognition (FER) [7, 13, 16]. However, the automatic
detection of expression based on human posture is an emerging
topic motivated by the recent ease to capture human motions; with-
out marker and with low price devices. Furthermore, psychological
studies show that the human posture is as powerful as facial expres-
sions in conveying emotions [21]. First, we present the classical
approaches based on features extraction, then we continue with
the different representation of motions in order to motivate our
approach.

Many existing approaches focus on very specific actions, as of-
ten done in psychology studies. Many papers have focused on the
locomotion [5, 14, 23, 24, 24], some on knocking actions [6, 11], on
artistic performance [25], or on talking persons [29]. Body move-
ments are characterized by a high dimensional configuration space
with many interrelated degrees of freedom. Psychologists’ stud-
ies have sought to understand body expression according to body
movements, i.e. form and movement. Two main levels of body
descriptors have emerged: high- and low-level descriptors. The
low-level descriptors provide features that quantifies the move-
ments (joint angles, 3D positions, distance between joints, velocity,
acceleration, etc.). We note a lack of common vocabulary in dif-
f erent papers whereas they use similar descriptors. The high-level
descriptors are very context-dependent and thus, are difficult to
compare in a general point of views. The most popular formalism
is certainly the one used to analyze dance movements proposed by
Laban and Ullmann [30]. The Laban analysis provides a consistent
representation of gestures expressibility. This model consists of
characterizing the body motion in terms of a fixed number of quali-
ties. The Laban model analysis includes five major qualities: body,
relationship, space, effort, and shape which allows summarizing
and interpreting movements with a small set of parameters.

Few state of the art papers tackle the analysis of heterogeneous
body movement. Kleinsmith et al. [18] proposed the UCLIC database
featuring 13 participants from different cultural regions, portray-
ing four emotions (anger, fear, happiness and sadness). Wang et al.
[31] proposed a real-time system that recognizes emotions from
body movements. They used a combination of low-level 3D pos-
tural features and high level kinematic and geometrical features.
They obtained a classification rate of 78% with a Random Forest
classifier on the UCLIC database, we will compare our method with
their results in the Section 4 for comparison. Truong et al. [27] pro-
pose a new set of 3D gesture descriptors based on a generalization
of the Laban descriptor model for gestures expressiveness. They
obtained a recognition rate for action recognition of 97% on the
Microsoft Research Cambridge-12 dataset [10]. They also tested
their classification approach on their own database which contains
882 gestures and achieved best F-Score of 56.9%. The F-score is a
measure of a test accuracy. Finally, Crenn et al. [9] proposed a new
set of two-levels 3D descriptors based on psychological studies.
They proposed low-level features which are based on visual cues,
and the high-level features are statistic operator in order to reduce
the feature vector size and compact the information. They have
evaluated their approach on different databases with heterogeneous
movements and body expression. They obtained a classification
rate of 93% on a synthetic database and results at par with state of
the art for another database.

We have presented different methods based on features extrac-
tion in order to recognize body expression. The main issue with that
kind of approaches is that they are not invariant to the movement
performed whereas it is very important given the high degrees
of freedom of the body. Indeed, most of the features used by the
different methods mentioned above are highly dependent on the
movement realized (speed, form, distance, etc.). From this conclu-
sion, we have modelized a style as an enrichment of a gesture. We
argue that separating the gesture from the expression is probably
an important point in the analysis of expressions in an movement.
Our method is inspired by the domain of the Computer Graphics
which used different representations of body movement and ges-
ture expressiveness to edit and generate new animations. These
editions of an animation can be done by time warping, editing speed
and spatial amplitude of the motions of body part joints [1, 12, 32].
Early in Computer Graphics, researchers [8, 28] proposed to edit an
animation as a signal using Fourier transform. Recently, with the
goal of transferring expressions between two animations, Yumer
and Mitra [33] proposed an approach which succeeds to transfer a
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style based on the residue obtains from the difference on the spectral intensity representations of reference and source styles for an arbitrary action. They showed that the difference in the frequency domain between an expressive motion and neutral one is highly correlated even though the actions are different. Our approach is inspired by their method as we believe that the spectral residue is more invariant to the movement than methods based on feature extraction.

3 PROPOSED METHOD

Our main focus in this work is to recognize body expressions independently of the movement performed. Our method is based on a neutral movement synthesis from a given expressive one. Our framework consists of two steps, the synthesis of the neutral motion and the classification based on the residue. As pointed out above, we assume that spectral difference between two movements contains the information for the extraction of body expression. The first problem consists to obtain a neutral animation from an expressive movement. The overview of our approach is given in Figure 2.

3.1 Neutral Animation Synthesis

The notion of neutral versus expressive movement is always linked to a context. Often understood as a sequence of actions without an emotional mark, a neutral movement may eventually be confused with a robotic movement. Our approach is based on a filtering of the trajectories of each articulation in order to reduce the oscillations in the expressive movement. The second step used inverse kinematics to produce a robotic motion without expression. Finally, we introduce a cost function that will compromise between joint filtering and inverse kinematics.

3.1.1 Body Joint Trajectory Smoothing. The input motion data are temporal samples of joint angles that represent the skeleton expressive animation. Our first step is to compute the joint trajectories in 3D and convert them in a cubic B-spline formalism. The B-spline curves are well-adapted for the operations of simplification we will apply on the trajectories to derive a neutral motion. The Equation of a B-splines is:

\[
S(t) = \sum_{i=0}^{m-n-1} b_{i,n}(t)P_i, t \in [0, 1]
\]  \hspace{1cm} (1)

where \( n \) is the order of our B-spline. In our case, we use the Cubic B-spline so we have \( n = 2 \). \( m \) is the number of control points. The points \( P_i \) form a polygon called the control polygon: the number of points making up this polygon is \( m - n \). These \( m - n \) functions B-spline of degree \( n \) are defined by recurrence on the lower degree:

\[
b_{j,0}(t) = \begin{cases} 
1, & \text{if } t_j \leq t \leq t_{j+1} \\
0, & \text{otherwise}
\end{cases}
\]

\[
b_{j,n}(t) = \frac{t - t_j}{t_{j+n} - t_j} b_{j,n-1}(t) + \frac{t_{j+n+1} - t_j}{t_{j+n+1} - t_{j+1}} b_{j+1,n-1}(t)
\]  \hspace{1cm} (2)

As a first step, we smooth the original trajectories of each body joints represented by B-spline. We decimate each B-spline by removing one control point from each curve. We reconstruct the B-spline with the remaining control points. Our method for smoothing the trajectory of body joint is presented is the Figure 3. As one can see from Figure 3, we remove one control point per curve, i.e. on each \( m - n \) functions. The position of the new control points is interpolated on each \( m - n \) functions with a parameter \( t \). On the Figure 3, we used \( t = 0.5 \).

Our iterative method has two parameters that control the number of iterations and the position of the new points by a cubic interpolation. The different levels of details which can be generated from the input trajectory are presented on the Figure 4. This simplification reduced the variation of the motion for each body joint trajectory. By analyzing lots of expressive movements in different databases, we have categorized two types of expressive trajectories: energetic (happy, proud, anger, etc.) and moderate (depressed, old, etc.) movements. A neutral trajectory is more "flatten" that an energetic trajectory, i.e. joint has less variations during the motion and can be clearly produced by this smoothing step. For the moderate movements the smoothing step does not change much the trajectory but the IK step during the optimization process presented in the next two Sections will edit the movement toward a neutral one.

Our method to smooth an input motion is presented on the Figure 5. The input motion is represented by the black curve, the B-spline obtained by our method is represented by the green curve and the ground truth B-spline is represented by the red curve. The ground truth curve is the neutral trajectory of the joint as provided in the databases including neutral movement. These curves show the right foot during a kicking action. With a simple pass of smoothing, we synthesize a new motion similar to the neutral motion. To obtain this neutral trajectory from the input expressive one, we have manually tweaked the simplifications parameters of the B-spline. Finding efficient parameters working on any kind of movements is manually unreachable. In the Section 3.1.3 we propose an optimization process based on a function which characterize a neutral motion. In addition to these parameters setting, the trajectories generated individually by this method do not guaranty that the constraints of the animation are respected like the constant length of the bones or the feet that do not slide on the ground.

3.1.2 Inverse Kinematics. Smoothing the B-spline of the joint trajectories is not sufficient to produce a neutral movement. First, the motion generated from the smoothing step does not respect the constant length of the bones and suffer from artifacts as feet sliding on the ground. To solve these issues, we apply an Inverse Kinematics (IK) technique. IK is defined as the problem of determining a set of appropriate joint configurations for which the end effectors move to the desired position as smoothly, rapidly, and as accurately as possible. We use the Fabrik algorithm proposed by Aristidou and Lasenby in [3]. Fabrik has the advantages to converge in few iterations, produces visually realistic poses and other constraints like non-foot-sliding can easily be included. In our method, we used Fabrik with Model Constraints [2] in order to represent a human-like model. The Model Constraints is an extension of the Fabrik method that proposed a human-like model using Fabrik.

The Algorithm 1 describes the different steps to synthesize a neutral motion from an expressive one and the different parameters used during the computation. This algorithm with an efficient set of parameters allows to synthesize a neutral motion from any kind of expressive motion. Even if it may produce a neutral motion which
could be a bit “robotic”, it is nevertheless efficient for the classification part, as confirmed by the recognition rate in Section 4. The algorithm has a set of 16 parameters in order to produce a neutral motion. Finding efficient values for these different parameters is not manually tractable for different motions on different databases.

Figure 3: Our method for smoothing a body joint trajectory based on a decimation of B-spline control points. Blue B-spline represents the original motion. Red B-spline shows the smoothed curve after one iteration, green B-spline after two iterations.

We have proposed an energy-based term which describes a neutral motion in the next Section and an optimization process provide parameters to generate a neutral animation.

3.1.3 Cost Function for generating a neutral motion. The several parameters of the trajectories simplification and the IK step are determined by a minimization process. For this purpose, we propose a function that characterizes a coarse neutral animation. For the purpose of an intuitive formalism we have designed the function as more the value returned by this function is small, more “neutral” the animation is. A neutral motion costs little. The minimization
**Algorithm 1: Algorithm for neutral movement synthesis**

<table>
<thead>
<tr>
<th>Input: $M_i$: Input Motion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data:</td>
</tr>
<tr>
<td>joints: a table of all body joints</td>
</tr>
<tr>
<td>trajectories: a table of all trajectories for each joint</td>
</tr>
<tr>
<td>trajectoriesSmooth: a table of all trajectories smooth for each joint</td>
</tr>
<tr>
<td>Result: $M_n$: Neutral Motion</td>
</tr>
<tr>
<td>Parameters: samplingValue: temporal parameter determining anchoring postures for the IK step</td>
</tr>
<tr>
<td>weightTargets: a table of weight that balance the IK goal (1 = at the goal and 0 = idle pose of our skeleton) for the rotation and position.</td>
</tr>
<tr>
<td>weightHints: a table of weight that balance the IK hint (1 = at the goal and 0 = idle pose of our skeleton) for the rotation and position.</td>
</tr>
</tbody>
</table>

1. **foreach** joint, $j$, in joints do
2.   trajectories$_i$ ← computeTrajectory$(j)$;
3.   trajectoriesSmooth$_i$ ← smoothTrajectory$(trajectories_j)$;
4. **end**

9. **foreach** EndEffector, end, in joints do
10.   indiceHint ← end$_i$.getParent();
11. **for** $i = 0; i < endTime; i += samplingValue$ do
12.     target$_{end_i}$ ← trajectoriesSmooth$_j$;
13.     hint$_{end_i}$ ← trajectoriesSmooth$_j$.indiceHint;
14.   **IK Step**( target$_{end_i}$, hint$_{end_i}$, weightTargets, weightHints);
15. **end**

The distances $D_o(j)$ and $D_s(j)$ covered by a joint $j$ during an action are given by the length of our B-spline. These distances are approximated by sampling multiple points on our spline and then calculate the distance between these points. The accelerations $E_o(j)$ and $E_s(j)$ of a joint $j$ gives us information about the energy spend by joint during the action. To find these accelerations, we are calculating the second derivative of each B-spline per joint.

**Implementation Details** The cost function is minimized iteratively using Particle Swarm Optimization (PSO). PSO has the advantage to require few or no assumptions about the function being optimized and can search in very large spaces of candidate solutions. The main issue with PSO is that the solution founded is not guaranteed to be the optimal solution. Based on our tests, finding a good solution instead of the optimal one is sufficient, since the coarse neutral animation is used for the differentiation with the expressive one before the classification. We have experimented different value of $\lambda$ (see Figure 6) and we have empirically found that $\lambda = 0.2$ is a good default setting for all databases.

### 3.2 Residue Between Neutral and Expressive Motion

At this stage, we have the original expressive motion and a coarse neutral motion obtained by optimizing the cost function. In order to extract the expression from the original input motion, our idea is to analyze the difference between the neutral and the expressive motion. This difference extracts the body expression invariant to

$$\text{Cost} = \sum_{j \in \theta} [(1 - \lambda)(D_s(j) - D_o(j)) + \lambda(A_s(j) - A_o(j))]^2$$  \hfill (3)

with $j$ represent a body joint, $\theta$ is the set of body joints of the input skeleton and $\lambda \in [0, 1]$ is a weight parameter. The influence of the factor $\lambda$, for the classification rate on the Siggraph database, is shown in Figure 6. With $\lambda = 0$, we are only using the distance term: and with $\lambda = 1$, we are only using the acceleration term.
The magnitude contains the information about the motion and the expression of an animation, it provides enough information. The residue forms the feature vector we use as input data of the classifiers in order to get the expression type. The classification rate given in the Section 4 is the ratio between the number of good classification divided by the number of tested animation. In our approach, we have to define the number of sampling of the input signal. The Figure 6 illustrates the variation of the classification rate (in %) with different sampling value. The classification rate decreases when the sampling value is increased, this is due to the fact that it increases the size of the feature vector which generate noise for the classifier. The size of our feature vector is given by the number of DOF in the skeleton multiplied by this sampling value of the input signal. We have set the sampling value to 8 for the Section 4.

4 RESULTS AND ANALYSIS

We have tested our method on four databases where characteristics are detailed in the Table 1. Three of them are acted databases, while the last one consists of synthetic animations generated by the method of Xia et al. [32]. We will refer the last database as the SIGGRAPH database in the rest of this paper.

(1) Biological Motion [20]. This database contains 4080 motions (walking, knocking, lifting and throwing) with 4 expressions (angry, neutral, happy, sad). Unfortunately, we used only a subset of 1356 motions, especially knocking as it is the set of motions available on the web. The state of the art presented in Table 2 uses the same set of motions we used. This database contains 15 male and 15 female amateur actors with a mean age of 22 years. Motions have been recorded using a motion capture system leading to a set of 35 body joints.

(2) UCLIC Affective Body Posture and Motion [18]. This acted database contains 183 animations with 4 expressions (fear, sad, happy, angry). This database contains 13 human subjects from different cultural regions. Actors were directed to perform the emotion postures in their own way. They used a motion capture system to collect 3D affective postures leading to a set of 32 body joints.

(3) MPI Emotional Body Expressions Database for Narrative Scenarios [29]. This database consists of 1447 motions of amateur actors narrating coherent stories. This database contains 8 actors, 4 females and 4 males with a mean age of 25 years. Actors were asked to imagine that they were narrating several stories to children. It contains 11 emotions (amusement, anger, disgust, fear, joy, neutral, pride, relief, sadness, shame, surprise). They used a motion capture system to collect 3D postures leading to a set of 22 joints. This database is highly imbalanced is terms of expressions. Joy...
is the most represented expression with 227 instances and shame is the less represented expression with 58 instances.

(4) SIGGRAPH database [32]. The SIGGRAPH database is a database used in synthesis of animation. They recorded 11 minutes of motion capture data. It contains 572 animations with 8 expressions or style (angry, childish, depressed, neutral, old, proud, sexy, strutting). Notices that the SIGGRAPH database includes the largest range of movements: jump, run, kick, walk, punching and transitions between these motions.

Table 1: Description of the databases used for the test of our method.

<table>
<thead>
<tr>
<th>Database</th>
<th>Number of movements</th>
<th>Number of expressions</th>
</tr>
</thead>
<tbody>
<tr>
<td>UCLIC [18]</td>
<td>183</td>
<td>4</td>
</tr>
<tr>
<td>Biological</td>
<td>1356</td>
<td>4</td>
</tr>
<tr>
<td>SIGGRAPH</td>
<td>572</td>
<td>4 and 4 styles</td>
</tr>
<tr>
<td>MPI [29]</td>
<td>1443</td>
<td>11</td>
</tr>
</tbody>
</table>

Figure 7 shows the influence of the size of the training set on the performance of the three classifiers used in our method. We compared the performance of our method with Support Vector Machine (SVM) with $\chi^2$ kernel, Random Forest with 100 trees and 2-Nearest neighbor based on Euclidean distance. Figure 7 has been produced on the SIGGRAPH database. For all the classifiers, we have computed the classification rate using different number of folds ($k'$) for the $k$-fold cross validation technique. The performance of our framework was evaluated using a conventional Random Forest with 10 folds and 100 trees as its achieved highest recognition rate. Results obtain with the Random Forest show how well our feature space was clustered. Table 2 shows the comparison of the achieved recognition rate of the proposed framework with the state-of-the-art methods using the same database. Table 2 illustrated that our framework exceeds state of the art methods in terms of expression recognition accuracy. Indeed, we are comparing our method with specific methods developed for one database containing often only on type of movement whereas our method is intended to be generic.

We have evaluated our approach on a PC i7-4710MQ with 8GB of Ram. The neutral animation synthesis take 180ms for a sequence of 2 seconds, with 120 frames, after running the optimization to find the parameters that satisfy the cost function. The optimization process takes 8 seconds for the same sequence of 2 seconds in C#. We believe that an optimized code can be real time.

Table 2: Comparison of our methods using all features mentioned in this paper to the state of the art methods. Notice that the specific method on the Biological database uses a dedicated algorithm to one kind of movements by computing an average motion and can not be generalized.

<table>
<thead>
<tr>
<th>Database</th>
<th>Results from state-of-the-art</th>
<th>Our results</th>
</tr>
</thead>
<tbody>
<tr>
<td>UCLIC</td>
<td>78% [31]</td>
<td>83%</td>
</tr>
<tr>
<td>Biological</td>
<td>50% (general) to 80% (specific) [6]</td>
<td>57%</td>
</tr>
<tr>
<td>SIGGRAPH</td>
<td>93% [9]</td>
<td>98%</td>
</tr>
<tr>
<td>MPI</td>
<td>–</td>
<td>50%</td>
</tr>
</tbody>
</table>

5 DISCUSSIONS AND CONCLUSION

We have presented a novel approach for automatic recognition of body expressions through 3D skeleton provided by motion capture data. We argue that body expressions can be robustly recognized by analyzing the difference between neutral and expressive animations in the frequency domain. One of the contribution of the proposed method is the synthesis of plausible neutral motion from an expressive motion, problem that was never tackle to our knowledge. Proposed method is able to generate a neutral motion from...
an expressive animation even in complex cases: jump, run, kick, etc. From the synthesized neural motion, proposed method classifies expressions of the input motion by computing the spectral difference in the Fourier domain between the neutral and expression motion. We have evaluated our approach on four databases that contain heterogeneous movements and expressions and obtained results that exceeds state of the art. Thus, our approach opens up many possibilities for human-computer interaction applications. One such application that can benefit from proposed approach is the generation of video games using the Kinect-like device. Computer games can benefit from real time body expression analysis to adapt its content at run time i.e. dynamic game play based on expressions exhibited by player’s body.

In future we aim to continue working on method that can generate more realistic neutral animations by adding a technique to change the timing of the neutral animation. This can be achieved by analyzing the phase of the neutral animation produced by proposed method. Another direction that we are looking forward to explore is the usage of the Quaternion Fourier Transform in order to have a more accurate signal information since the joint channels are processed in a single unit. Finally, an improvement of the validation will be to test our approach on multi-simultaneous actions during a real live demonstration with a Kinect for instance.

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