Emotional Control of Virtual Characters during Locomotions

Diogo Silva
Instituto Superior Técnico
Universidade de Lisboa
Lisbon, Portugal
diogo.goncalves.silva@tecnico.ulisboa.pt

Pedro A. Santos
INESC-ID & Instituto Superior Técnico
Universidade de Lisboa
Lisbon, Portugal
pedro.santos@tecnico.ulisboa.pt

João Dias
Faculty of Science and Technology
University of Algarve
Faro, Portugal
jmdias@ualg.pt

***Abstract*—Equipping a virtual character with the capability to express a wide array of emotions is paramount to making that character seem believable, realistic and for it to provoke, in the viewer, the artist's intended impact. This emotional expression can be done in a multitude of ways, but one of the most habitual is through nuances in the character's body language. This can be accomplished by producing several variants of the same baseline animation for each different emotion. A problem with this methodology, however, is that it is not scalable. As the number of motion-emotion pairings increases, so does the amount of animations that must be created, either manually, or through the usage of new systems for automatic animation generation. Furthermore, reference motion capture data of an actor conveying the same movements in each desired emotion must be readily available. We propose a solution to this problem in the form of a tool that is not only capable of identifying the perceived emotion of virtual character locomotion animations but that can also synthesize and apply the required bodily changes in order to alter the character's expressed emotion, in real time.**

***Index Terms*—computer animation, machine learning, kinematic models, physics-based models, sentiment analysis, motion synthesis**

I. Introduction

Conventionally, 3D computer character animation is created by professional human artists who manually tweak a given character's body in key frames and interpolate between them. This process is commonly aided by the usage of motion capture data (mocap). These consist in recordings of human actors done in a way that their motions can be directly applied to a virtual character. This data, when available, can be used as the basis for the animation and heavily aids the artist in speeding up the animation process.

Physics-based character animation generation has been growing in popularity due to its ability to synthesize realistic and natural-looking motions using only reference mocap files, without the need of manual animation work. Recent advancements made in Deep Reinforcement Learning (DRL) algorithms have allowed for the construction of such systems [9], [12], [14], able to successfully learn and reproduce physically accurate motor skills in a plethora of motions such as dances, locomotion and other such body gymnastics.

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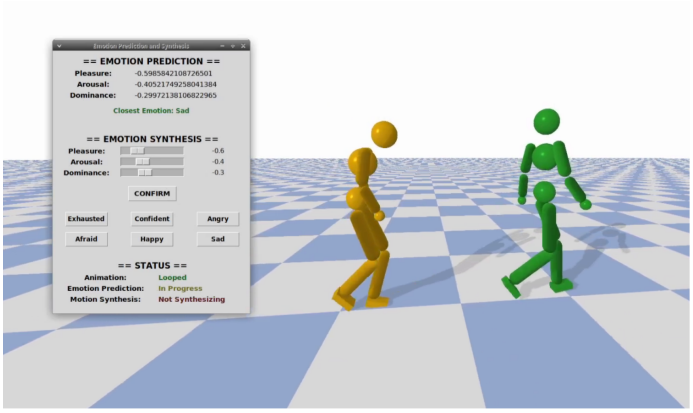

Fig. 1. The proposed system showcasing a reference baseline motion (right) and a physics-enabled policy-controlled character (left) whose movement has been altered to showcase the desired emotion "Sad".

However, one problem both these systems and traditional mocap driven animation struggle with is having the character express different emotions using the same motion. Styles and emotions are an important aspect of generating realistic, believable virtual characters. Animators are usually tasked with not only creating the baseline movement for the animation, but also controlling the character's body language in order to convey different emotional states, feelings and styles. Such expressiveness is paramount to properly conveying a story, setting a scene's tone and making it so the virtual character has an actual impact on the viewer.

The problem then lies in the fact that, should animators want their character to convey different emotions, they would need to record actors portraying the same motion in all desired emotions. For example, if an animator wants a character to walk sadly, happily and angrily, they need to gather mocap data of the same walking animation but with the actor conveying sadness, happiness and anger. They then need to generate an entirely new animation for each emotion, either by training a motion learning system or through manual computer animation. This process has to be repeated each time the animator wishes for their character to express a new emotion - if they now want their character to convey the feeling of pride they need to once again get more mocap data and generate a whole

new animation to add to the stack.

We propose a novel solution to this problem that combines the usage of Machine Learning (ML) models and Laban Movement Analysis (LMA) [7] for emotional classification and motion generation. Changes to the motion are applied in real time and get computed after a new desired emotion is specified. New poses are synthesized for the character at each frame, forcing the character to express the desired emotion, whilst still maintaining the baseline motion and movement.

The developed framework, shown in Figure 1, focuses on locomotive motions - walking, running and dashing - and allows users to edit the virtual character's expressed style and emotion in real-time, any number of times, without slowing down or stopping the animation and without the need for any additional mocap data or motion learning training. Moreover, our system works not only with Kinematic mocap data but also automatically generated Physics-Enabled Policy based character controllers learnt using the Spacetime Bounds DRL system [12].

II. Related Work

A. Motion Learning

There have been numerous efforts poured into creating virtual character controllers that can automatically learn how to mimic and perform animations without the need of human animators. Earlier approaches focused on purely data-driven Kinematic Models generated by neural networks [11], [19]. More robust solutions based around Physics-Based models [1], [5], [14], [23] offered the guarantee of generating physically accurate motions. The state of the art now lies in the usage of Reinforcement Learning methodologies for the generation of physics-based character controllers. Systems such as ***DeepMimic*** [14] proved the efficacy of such techniques in creating policy-based character controllers able to imitate motions, provided via motion capture data. ***SpacetimeBounds*** [12] further iterated on the ideas of DeepMimic through the introduction of loose space-time constraint used to limit the training search space in a fashion akin to early termination. These restrictions bind the character's states in space and time during the reinforcement learning training process based only on the given reference motion. Additionally, by loosening or tightening the spacetime bounds, this system allows users to indirectly curate the look and feel of the outcome motion, hence providing a manner of style exploration.

An issue with SpacetimeBound's stylistic exploration is that after the character controller policy has been learned, there is no way to further edit the character's style or emotion. This issue is prevalent in all of the aforementioned systems which focused on learning to mimic the given references rather than empowering the character with the capability of expressing the same motion in a wide array of emotions. Our work aims to fix this issue by allowing users to edit and swap the learned animation's expressed emotion in real time, without the need of additional references or further training.

B. Motion Analysis and Tweaking

Emotional classification involves manners of distinguishing emotions from one another. There are two main approaches to emotion classification - one in which emotions are considered discrete, meaning humans have a preset array of emotions that they discretely swap between [10], [20], and one in which emotions are defined in accordance to continuous values in dimensional axis, blending into each other smoothly [13], [18]. Focusing on the latter, there are several dimensional models that attempt to place emotions on a 2D or 3D scale. Russel's Circumplex Model (RCM) [18] is one such model which maps emotions into a 2 dimensional space consisting of an Arousal and Valence axis, describing emotions alongside a Deactivated/Alert and a Pleasure/Displeasure continuum. The ***Pleasure, Arousal, Dominance Emotional State Model*** (PAD) [13] is an extension of the ideas of RCM, adding a new emotional dimension - Dominance. This new axis allows for a more granular specification of the character's emotion, accounting for the emotional impact of external forces upon the actor's feelings.

Motion analysis focuses on parameterizing and describing a character's movements. ***Laban Movement Analysis*** (LMA) is one such motion analysis methodology capable of describing human movements by drawing inspiration from fields of anatomy, kinematics and psychology [2], [7]. LMA breaks down movement description into 4 categories - Body, Effort, Shape and Space - each possessing different properties. Recent efforts have been able to utilize LMA features to accurately assess the discrete emotion of different gaits by further splitting the LMA features into Posture, and Movement features [16].

A noteworthy approach to motion analysis and tweaking is the one proposed by Aristidou et al. [2]. These authors developed a system capable of extracting a motion capture's select set of LMA features and mapped them into the RCM emotional coordinates through Linear Regression. They also managed to achieve the inverse process of mapping 2D emotional coordinates back into a set of LMA features. These generated LMA features were then fed into a Heuristic-Rules based motion synthesis algorithm, transforming them into joint rotation changes that could then be applied to the virtual character using Inverse Kinematics. Our system draws a lot of inspiration from this one but presents several key changes. Firstly, instead of focusing on contemporary dance motions our efforts diverged towards locomotion animations. Rather than using the RCM model we utilized the more descriptive PAD model [13]. Furthermore we utilized Gradient Tree Boosting Regression for LMA to PAD mapping and proposed the usage of both Gradient Tree Boosting Regressors and an Autoencoder to reduce the dimensionality of LMA features when mapping from PAD to LMA. Finally, the system allows for the emotional identification and tweaking of not only mocap driven kinematic controllers, but also policy-controlled physics-based characters.

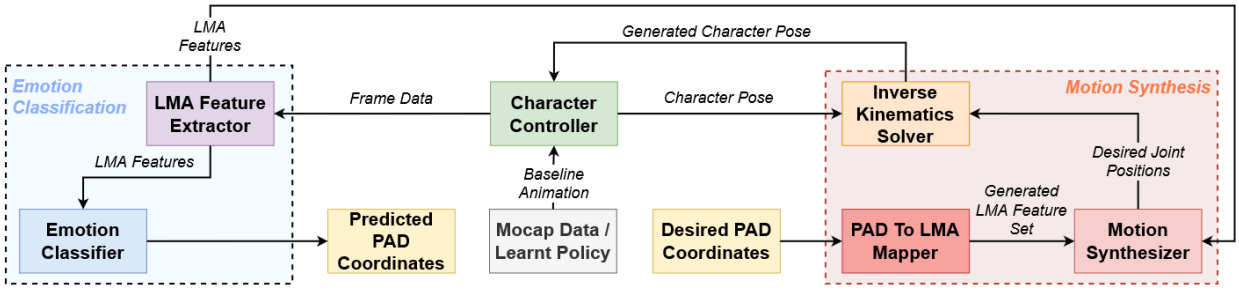

Fig. 2. An overview of the system's architecture. For Emotion Classification, the system begins by computing a set of LMA features from the frame data extracted from the character. These features are then fed to the Emotion Classifier module which outputs the predicted PAD coordinates. When new desired PAD coordinates are specified they first get converted into a set of LMA Features. This is then given to the Motion Synthesis module which computes new desired joint positions that are then used by the Inverse Kinematics Solver to generate the character's new pose.

III. Emotionally Expressive Motion Controller

The Emotionally Expressive Motion Controller (EEMC) system can be subdivided into several core sub modules. Figure 2 illustrates the connections between the modules and the system's overall architecture. At the core of the system lies a character controller used to make a character execute the intended baseline animation. This controller can either be Kinematic, driven directly by provided mocap, or Policy-Based Physics-Enabled learned, for instance, using the Spacetime Bounds [12] or DeepMimic [14] system.

For Emotion Classification, the system begins by computing a set of LMA features from the frame data extracted from the character. These features are then given to the Emotion Classifier module which, being empowered with a set of ML models, outputs the predicted PAD coordinates.

Emotional Motion Synthesis is triggered whenever new desired PAD coordinates are specified. Firstly, the system converts the new coordinates into a set of LMA features using ML. These features, alongside all of the baseline animation's LMA features, are then given to the Motion Synthesis module which computes new desired joint positions. These, plus the character's current pose, are then provided to the Inverse Kinematics Solver module to generate a new pose for the character.

A. Dataset

The **Bandai-Namco-Research Motion Dataset** [3] was utilized to train each of the system's ML models. This data consists of Bounding Volume Hierarchy (BVH) files describing a wide array of motions such as walking, running, kicks and dances running at 30 frames per second. Each animation was performed in order to convey a specific style like proud or masculine. Before usage the dataset was first culled and prepared using the pipeline described in Figure 3.

The original dataset's labels were mapped into corresponding emotions and PAD coordinates [8]. The values chosen for the emotional coordinates were inspired by previous discrete emotion to PAD mapping efforts [2], [8], [24] with minor adjustments to better fit the dataset's animations. This resulted in **468 different animations in 14 emotions**, exemplified in Figure 4.

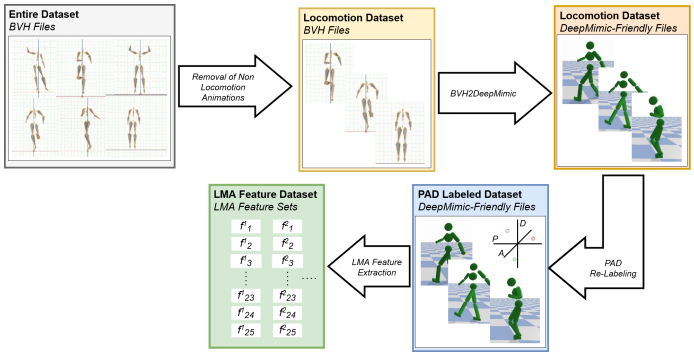

Fig. 3. The process of converting the Dataset's BVH files into a collection of usable LMA Feature sets.

Upon labeling each of our animation files their LMA Features were extracted. First, each frame's pose information (joint positions, velocities and rotations) gets stored. At each keyframe - every 5th frame - the stored data is then used to compute the LMA features corresponding to these past frames. Each set is composed of **25 different LMA features** as specified in Table I. A total of **78551 LMA Feature Sets** were retrieved, each labeled according to their PAD coordinates.

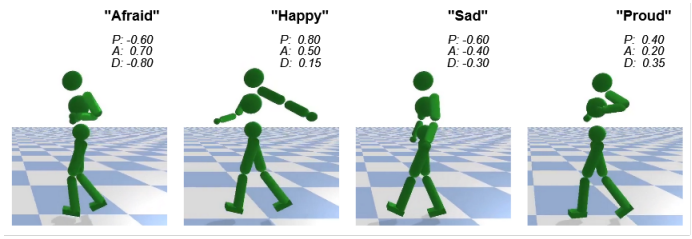

Fig. 4. Example of 4 motions from our dataset expressing 4 different emotions.

TABLE I
OUR SET OF 25 LMA FEATURES

LMA Feature	f	LMA Category
Max Hand Distance	f_1	Body
Avg. Left Hand - Hip Distance	f_2	Body
Avg. Right Hand - Hip Distance	f_3	Body
Max Stride Length	f_4	Body
Avg. Left Hand - Chest Distance	f_5	Body
Avg. Right Hand - Chest Distance	f_6	Body
Avg. Left Elbow - Hip Distance	f_7	Body
Avg. Right Elbow - Hip Distance	f_8	Body
Avg. Chest - Pelvis Distance	f_9	Body
Avg. Neck - Chest Distance	f_{10}	Body
Avg. Total Body Volume	f_{11}	Shape
Avg. Lower Body Volume	f_{12}	Shape
Avg. Upper Body Volume	f_{13}	Shape
Avg. Area between Hands and Neck	f_{14}	Shape
Avg. Area between Feet and Hip	f_{15}	Shape
Left Hand Speed	f_{16}	Effort
Right Hand Speed	f_{17}	Effort
Left Foot Speed	f_{18}	Effort
Right Foot Speed	f_{19}	Effort
Neck Speed	f_{20}	Effort
Left Hand Acceleration Magnitude	f_{21}	Effort
Right Hand Acceleration Magnitude	f_{22}	Effort
Left Foot Acceleration Magnitude	f_{23}	Effort
Right Foot Acceleration Magnitude	f_{24}	Effort
Neck Acceleration Magnitude	f_{25}	Effort

B. Emotional Classification

To classify the motion's perceived emotion a set of Gradient Tree Boosting Regressors were trained to map LMA Features into PAD coordinates. We used 3 regressors - one for each emotional coordinate - that took as input our set of 25 LMA Features and outputting the corresponding predicted coordinate. Figure 5 illustrates this process. Regression was chosen over classification due to the fact that the PAD Model identifies emotions according to their Pleasure, Arousal and Dominance values which are continuous.

The models were built using XGBoost [4]. Our dataset of LMA Features was first standardized and then shuffled and split into a train and test set. 80% of data was used for Training (62841 samples) and 20% was used for Testing (15710 samples). Hyper parameter tuning was done individually for each of the 3 regressors using Random Search 10-Fold Cross Validation. The final models managed to accomplish a mean absolute error of 0.02, 0.06 and 0.03 using the Test set for the Pleasure, Arousal and Dominance coordinates correspondingly, with values ranging between $[-1.0, 1.0]$. The predicted emotional coordinates of 1000 random samples from our Test set are shown in Figure 6. As can be seen, some predictions do stray slightly from their real coordinates, but they nevertheless fall into well defined emotion clusters and seldom stray from the correct octant in the 3D model.

It should be noted that mocap data consists of high-frequency "continuous" time series, in the sense that frames from the same animation are neighbours of each other and may present some form of sequential similarities. This same line of thought can be extended to our LMA Feature dataset. This may lead to an issue where, when data is randomly split as aforementioned, the train and test sets end up containing neighbouring LMA feature sets belonging to the same animation. This in turn could mean that the final results obtained over the test set could be good, solemnly because the models are overfitting to the train data, and the test set is comprised of similar features. To counteract this, and to make sure that the PAD regressors were not performing well simply due to dataset overfitting, we experimented with splitting animations directly into either the train and test set, rather than doing the aforementioned LMA Feature-level split. This means that the LMA Feature sets in the train set come from entirely different animations from those in the test set, effectively removing the "frame neighbour similarity" issue. The regressors were then trained and tested using these new dataset splits. Effectively, there was no apparent major performance hitThe reason as to why the sequential similarity nature of frame data seems to be a non-issue may be due to the fact that our models

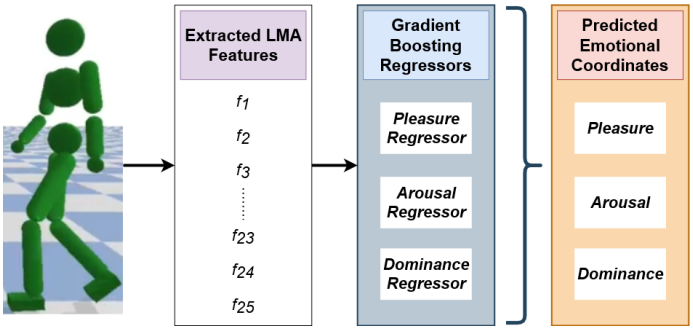

Fig. 5. The process of using our Gradient Boosting Regressors to predict the PAD coordinates of a set of LMA features extracted from a motion

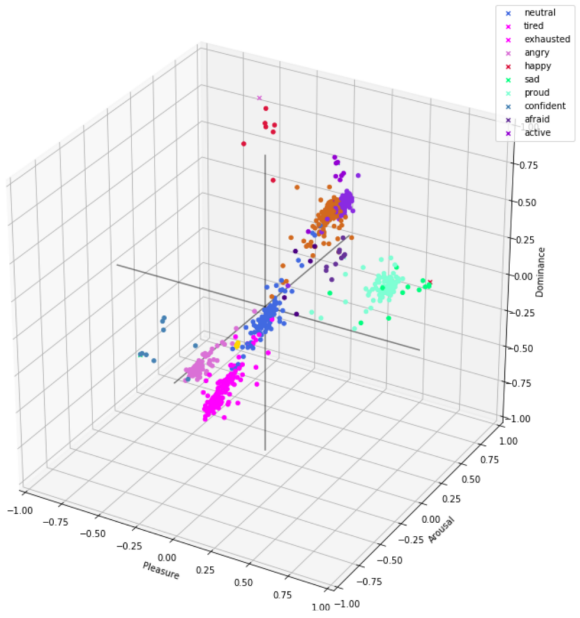

Fig. 6. Prediction results of samples from our Test set. Each sample is coloured according to their real emotion.

are not being trained with frame data directly, but instead using LMA Features extracted every fifth frame. As such, two neighbouring LMA features represent a higher time difference.

Using the trained predictors it is then possible to identify a given motion's perceived emotion in real time. During an animation's playtime LMA Features are extracted at every keyframe. After a list of 10 LMA Feature sets has been stored a new multithreaded process is started. This process standardizes the features and uses the predictors to compute the Pleasure, Arousal and Dominance coordinates for each of the sets. Each coordinate's predictions is then averaged, stored and output. At the end of the animation the final emotional prediction gets computed using a weighted average of all past predictions. For this average, the highest absolute recorded value for each emotional dimension is given a slightly higher weight. This stems from the assumption that the intensity of the intended emotional expression can vary throughout the course of the animation, but it will at some point reach a maximum absolute value, indicative of the feeling the character is aiming to express.

C. LMA Feature Generation

After training the LMA to PAD models, they were then used to generate a new dataset. This dataset stored our sets of LMA Features as target variables and their predicted PAD coordinates as inputs. New models capable of synthesizing new LMA Feature values from given PAD coordinates were trained using this data. First, an *Autoencoder* was created to convert the 25 LMA Features into a 5 dimensional Latent Feature space - l_1, l_2, l_3, l_4, l_5 - and vice-versa. This was done to decrease the overall complexity of the PAD-LMA mapping problem [21], [22]. A set of 5 Gradient Tree Boosting regressors was then trained to map PAD coordinates into each of these Latent Features. Figure 7 shows the process of generating new LMA values. The PAD coordinates are converted into Latent Features which in turn get decoded by the AutoEncoder into a set of corresponding LMA Features.

The Autoencoder Neural Network was built with the architecture illustrated in Figure 8. After training for 1024 epochs, it accomplished a mean absolute reconstruction error of 0.17 on the test set. We then generated a new labeled dataset using our PAD coordinates as input and the latent features created by the Autoencoder as output. This new dataset was used to train 5 regressors built using XGBoost in a manner similar to the predictors for Emotional Classification. Through this process we achieved an overall mean absolute error of 0.19 between the predicted emotional coordinates of the generated LMA Feature set and the original ones, with Pleasure an error of 0.19, Arousal 0.24 and Dominance 0.14.

D. Motion Synthesis

Given a new set of desired PAD coordinates it is possible to synthesize and apply motion changes to the character in real time. This editing can be performed multiple times and is done in a multithreaded process so as to avoid interrupting or slowing down the current animation's display. We designed

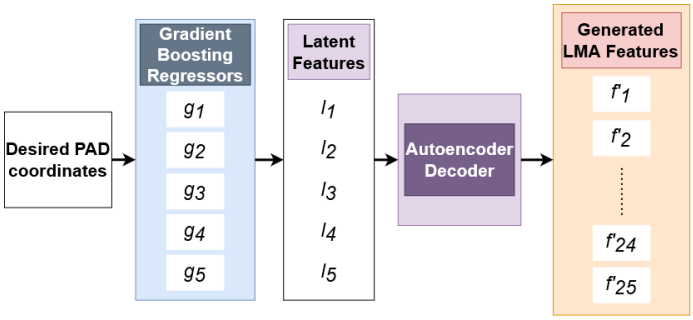

Fig. 7. Generation of LMA Features from PAD coordinates.

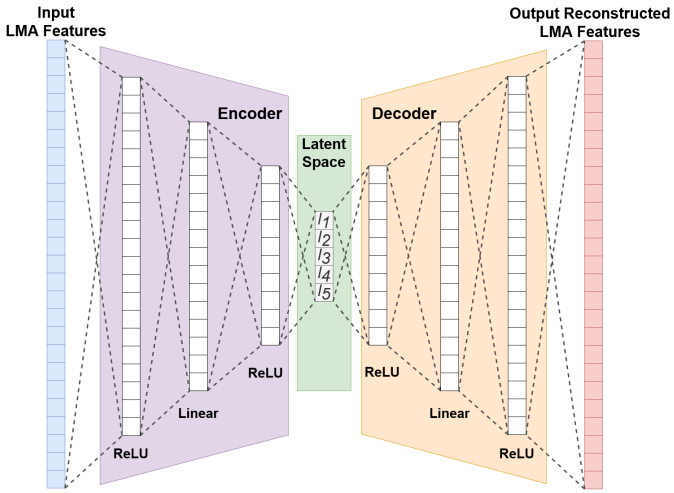

Fig. 8. The Autoencoder architecture.

a set of 6 Heuristic Rules, each responsible for tweaking the position or rotation of one of our core joints - Hips, Chest, Hands, Elbows, Feet and Neck. Changing upper body joints was the main focus as these tend to have the most impact on the conveyed emotion, while lower body joints are more important for balance and motion integrity rather than expression [2]. A subset of our rules can be seen in Figure 9. Each of these rules works by taking into account the current position or rotation of the joint its trying to change and one or more associated coefficients. The underlying idea behind each heuristic rule is that, by comparing the baseline animation's LMA features - which reflect the character's current emotion - with the generated ones - which correlate to the new desired emotion - we can then use coefficients to decide in which manner each joint should be altered. To exemplify, rule 1 - g_1 - changes the hips' height. The coefficient associated with rule 1 represents a comparison between relevant baseline and generated LMA Features. If this coefficient value is larger than one then that means that the current animation's associated LMA Features are smaller than their corresponding generated counterparts - chest-pelvis height, body volumes and so on - and as such, we want to increase them by increasing the hip's height and vice-versa. Every other rule was designed in a similar manner.

Rule	Affected LMA Features
$g_1(c_1)$: Modifies the hips height $r'_x = r_x$ $r'_y = r_y + (c_1 - 1.0) * 0.08$ $r'_z = r_z$ Where r is the current pelvis position and r' is the new desired pelvis position	c_1: f_9, f_{11}, f_{12}, f_{15}

$g_2(c_2)$: Modifies the chest position
if $c_2 > 1.0$:
$w = 0.025$
else:
$w = 0.1$
$n'_x = n_x - (c_2 - 1.0) * w$
$n'_y = n_y + (c_2 - 1.0) * w$
$n'_z = n_z$
Where n is the current chest position and n' is the new desired chest position
	c_2: f_9, f_{11}, f_{13}

Fig. 9. 2 of our 6 Motion Synthesis rules.

Whenever a new set of PAD coordinates is provided, new values for our set of LMA Features are created. These generated LMA Features. together with the animation's recorded LMA features, are utilized to compute the coefficients used in our heuristic rules. Each rule is associated with a different subset of LMA Features and its associated coefficients are computed by finding the value that minimizes the distance between the corresponding subset of recorded and generated LMA features. For example, rule g_1 aims to modify the position of our hips joint. To compute c_1, the coefficient associated with rule g_1, we find the value that minimizes the difference between the values of all recorded and generated LMA features that pertain to the hips. Looking at Figure I, for coefficient c_1, these features include $f_9, f_{11}, f_{12}, f_{13}$ and f_{15}. All coefficients are initialized at 1.0 and are minimized using Powell's method [15].

After computing the coefficients for each rule, the system then synthesizes the changes to the pose necessary to convey the desired emotion. If the character is being controlled by a learnt policy that means all poses are newly created at each frame. As such to get each frame's baseline pose we wait for it to be generated and interject it just before it gets applied to the character.

The heuristic rules are given the currently extracted pose to generate new core joint positions. These positions get handed to the Inverse Kinematics module to compute a new pose that attempts to get the core joints as close as possible to their desired synthesized positions, while still respecting the character's body restraints to avoid unnatural postures. The generated pose is then applied to the character, replacing the baseline pose and thus altering the character's emotional expression.

IV. Final System

Our system was built in Python 3.8, using PyBullet [6] as the underlying engine. All machine learning models were trained offline in a dedicated external server. Emotional Classification and Motion Synthesis is done in multithreaded processes and takes, on average, less than 3 seconds to execute and apply, running in real time. The system's test results, project code and other resources, were made publicly available[1].

To illustrate the functioning of our EEMC system the Graphical User Interface (GUI) shown in Figure 10 was developed. Users are shown a window with the virtual character performing the specified motion. They can pan the camera around and zoom in and out. If the user specified a policy-based character controller an additional character is also placed alongside the main one, showcasing the reference motion the policy learned from. The GUI shows the current results of the Emotional Classification by displaying the predicted Pleasure, Arousal and Dominance coordinates. To specify new desired PAD coordinates the user can freely tweak the corresponding sliders or select one of the available presets. Hitting the confirm button triggers the Motion Synthesis with the coordinates currently on the sliders. Aside from this, system state information is also showcased. Specifically, the GUI indicates whether the animation is running, has looped or has stopped, whether Emotional Classification is still ongoing or has finished and whether a new motion is being synthesized or not.

Triggering the Motion Synthesis module will alter the character's motion in real time. Figure 11 showcases 4 generated motions synthesized from the same baseline animation. The "Confident" character, for example, highly elevates their shoulders, widens their upper body volume and exposes their neck, while the "Afraid" character raises their arms to protect their torso and slumps down, reducing its body volume. Our synthesis works best when applied to a neutral baseline movement but it nevertheless works with different base emotions. Both our emotional classification and our synthesis were trained and designed for locomotion-type motions, specifically walking and running. Whilst they can still be applied to other types of animations without additional changes, the results won't be

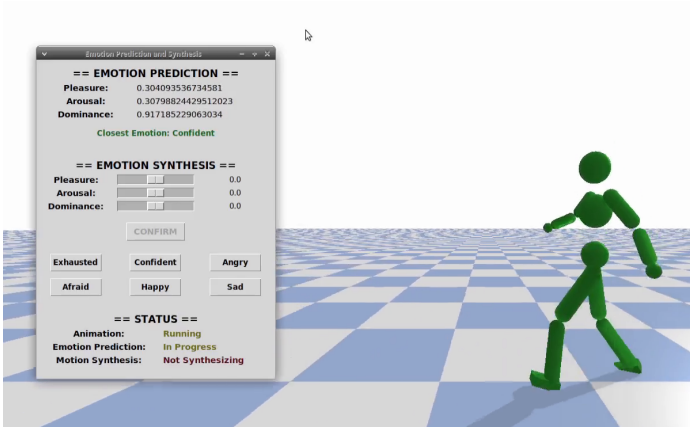

Fig. 10. Our system displaying motion capture data and our Graphical User Interface showing the current Emotional Prediction, system state and Motion Synthesis controls.

[1]https://heroufenix.github.io/expressive_animations_web/

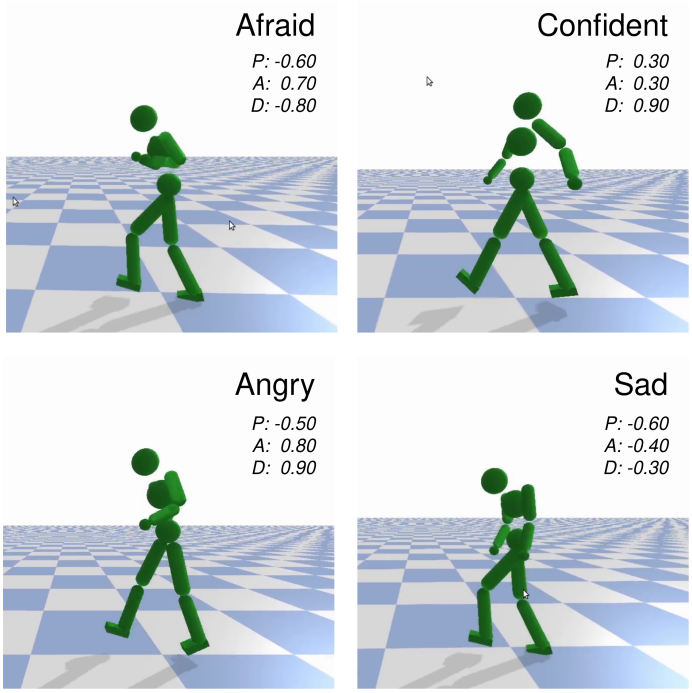

Fig. 11. Four motions synthesized using the same baseline motion and 4 different desired emotions.

as consistent. Motion Synthesis seems to suffer the most from this in the quality of the generated motions, mostly due to the fact that our heuristic rules were purposefully tweaked for locomotions. The Emotional Classification also suffers in the accuracy of its predictions but still manages to, more often than not, predict the correct emotional octant.

V. Results

User tests were conducted in order to evaluate the performance of the Emotionally Expressive Motion Synthesis. We wanted to evaluate how the generated motions would compare against the ones from the Bandai-Research Motion Dataset [3]. These reference motions were recorded with professional paid actors performing motions in very specific emotional styles. Our aim was to infer the synthesized motions' quality by checking if there were any major statistical differences between the answers users gave when presented with reference animation clips versus the generated ones. Furthermore we also wanted to compare the two LMA Feature generation approaches to understand if one outperformed the other in terms of emotional expression quality as perceived by users.

A set of video clips was created using our motion generation over both a Kinematic and a Policy-Controlled physics enabled character. Motions were generated to convey a subset of the Bandai-Research Motion Dataset's [3] emotions covering a wide spectrum of the PAD model - "Sad", "Confident", "Tired", "Afraid", "Angry" and "Happy". Every motion was generated by altering the same base "Neutral" walk animation. The overall intent was to check whether the generated motions managed to convey their intended emotions as well as the reference mocap. To infer these, two distinct tests were conducted with 40 anonymous, paid participants each. The tests consisted of online forms containing the aforementioned recorded animation clips mixed together and sorted randomly. Clips had their names redacted and participants were never informed or able to tell the type of clip - reference mocap or synthesized applied to either a kinematic or policy-based.

A. Emotion Identification Task

The first set of participants were asked to view each clip and select which emotion they thought the character was trying to express from a given list. The goal was to provide an initial insight towards how easy the generated motions' emotions were to identify. As such, a clip's performance is better the higher the percentage of participants that manage to correctly guess the character's intended emotion. For example, if a character is attempting to convey the feeling "Angry", the more participants that answer with "Angry", the better that clip performed. The quality of each generation technique was then ascertained by comparing its performance against each other and, more importantly, against the reference mocap.

The results were gathered in the clustered bar charts shown in Figure 12. Looking at the reference mocap, most participants managed to correctly identify the emotions "Afraid", "Confident", "Happy" and "Tired", although not by a vast majority in most cases. Compared to mocap, the generated motions applied to a Kinematic character managed to output better results, with the correct emotions being the most selected in all cases but "Tired" which nearly tied with "Sad". As for the generated motions applied to a Policy-based controller, the best performing emotions were "Confident", "Sad" and "Tired" with the remaining ones being in second or third place. In general, both generated models had similar performances comparatively to each other and to the reference mocap data.

B. Primed Emotion Agreement Task

Certain emotions have intrinsic ambiguity when lacking context [17], which might have influenced the answers given in the first test, explaining some of the obtained results. "Tired" and "Sad", for example, are both very low energy emotions and the way they get conveyed is somewhat similar, especially in the reference mocaps. As such, when presented with just the clip with no further context or information about what the character's intentions are, it becomes easy for users to mix these emotions. To counteract this, a second test was conducted where participants were explicitly told which emotion the character was trying to express. They were then asked to rate how much they agreed that the character was in fact expressing said emotion. Participants could answer using a Likert scale from 1 (Completely Disagree) to 5 (Completely Agree). The overall goal of this test was to infer how accurately each clip managed to convey their intended emotion, as perceived by the participants. As such, clips perform the better the more participants agree that the presented emotion accurately matches the one showcased by the character in its motion.

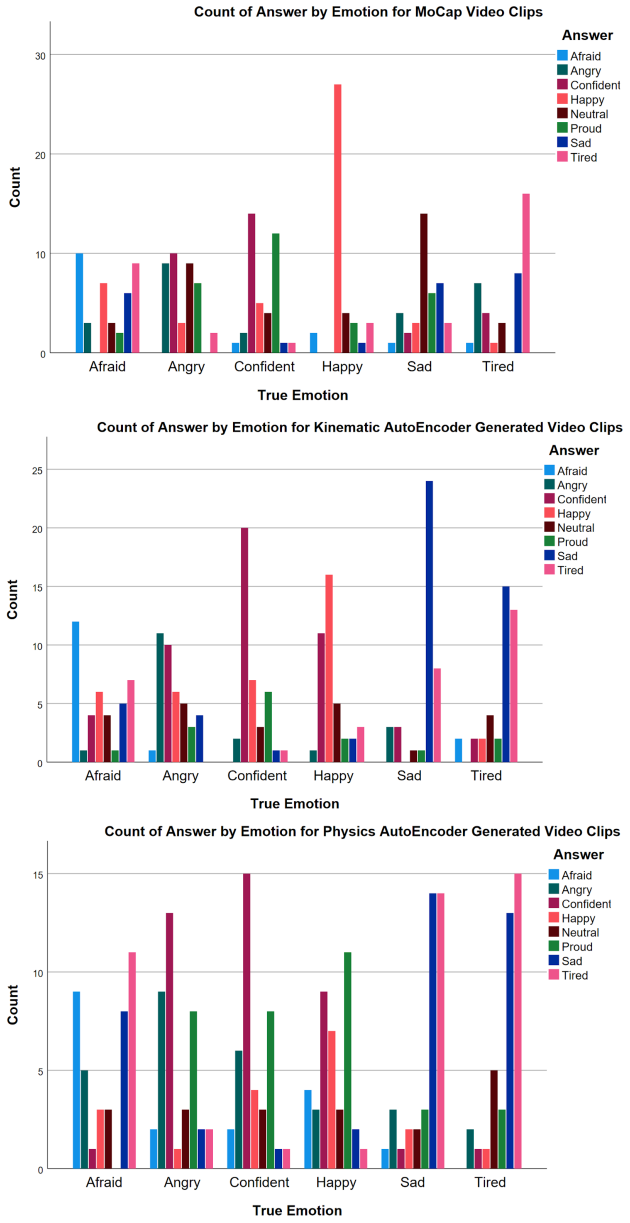

Fig. 12. Clustered bar charts showing the count of answers compared to the correct emotion for each type of clip.

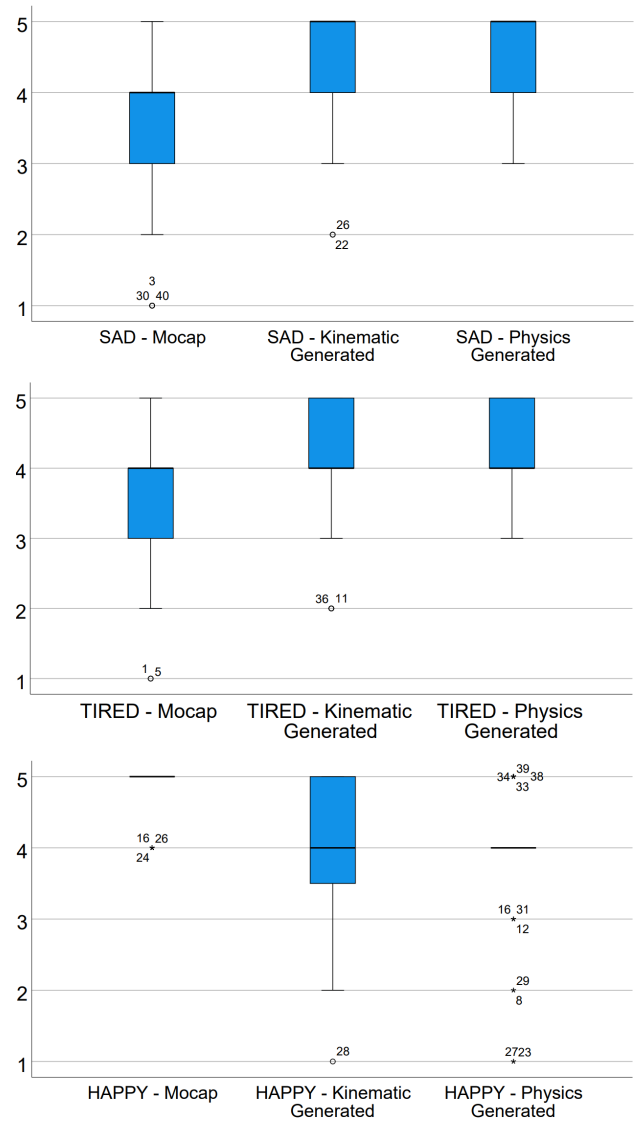

Fig. 13. Boxplot charts showing the value distribution for the emotions "Sad", "Tired" and "Happy" in regards to each type of clip.

An initial Friedman test done for each emotion showed that there was no statistically significant difference between our video clip types for "Afraid" ($p = 0.519$), "Confident" ($p = 0.121$) and "Angry" ($p = 0.657$). An additional Wilcoxon Signed Rank Test on the remaining emotions - "Sad", "Tired", "Happy" - confirmed, for all cases, a statistically significant difference between the generated motions and the reference mocap ($p < 0.001$). Figure 13 exemplifies the dispersion of answers per type of clip for the emotions where a statistically significant difference between the type of clip was found. For the "Sad" and "Tired" emotions, both types of generation actually outperform the reference mocap meaning that for these particular emotions, our generated motions are more easily identified as their corresponding emotions. For the emotions "Confident" and "Angry" the results were similar regardless of the clip being of a mocap or a generated motion. On the "Afraid" emotion we can see that the generated motion applied to the policy-based character performed slightly worse, but when applied to a kinematic character it still presented results similar to the reference mocap. The "Happy" emotion was the only one in which mocap outperformed our generated motions, although they still had decent results with most participants agreeing that the character was in fact exhibiting "Happiness".

C. Discussion

Looking at the results of both tests, participants, for the most part, managed to correctly identify and tended to agree with, the emotions that the generated motions were trying to convey. Moreover, certain emotions were more easily iden-

tified comparatively to the reference mocap. This showcases the efficacy of our system, as it proves that we can achieve results with similar emotional expressiveness to professional-grade mocap without the need and costs of recording several actors performing each of the desired emotions.

In terms of character controller type, both Kinematic and Policy-based character controllers seemed to present comparable performances. The obtained results didn't seem to deviate much within generation method as there was never an instance where results drastically changed depending on the character controller's type. This seems to indicate that the EEMC system can be effectively used regardless of controller type broadening its range of application to not only conventional mocap-based kinematic animations but also automatically generated policy-controlled learned motions.

VI. Conclusion

We have showcased our system for Emotional Classification and Emotionally Expressive Motion Control of Locomotion animations. We have proven that, through the usage of select LMA features we can accurately identify a character's expressed emotion in the 3D PAD Emotional space. We also managed to create a methodology for generating a new set of LMA Features with desired emotional values and use it to alter a character's motion in real time and without requiring any additional data or training. Furthermore, our system works not only on Kinematic controllers driven by mocap, but also on physics-enabled characters controlled by learnt policies.

Our system's value lies in the fact that we can alter a motion's emotion in real time without the need for any further data or training. Our system bypasses the need of having to record a mocap or train a character controller policy for each emotion that the character is meant to express over the same motion by managing to change the character's emotion instantaneously while its still performing the baseline movement. The fact that the system can be used interactively and that changes and predictions are output in real time means that users can be used not only to create new animations that could then be extracted and used just like conventionally generated ones, but could also be integrated with applications that require modifications to be done during run time.

To showcase our emotional classification and expressive motion editing we also designed an easy to use and interactable GUI that allows users to alter a baseline motion's emotion by specifying new desired PAD coordinates in real time and without the need for any specific domain knowledge. It should be noted, however, that this interface serves only to illustrate the underlying framework's capabilities, which could be used independently in professional applications.

In terms of future improvements, the dataset we used grouped animations into preset styles rather than emotional coordinates. As such, all animations that aimed to express the same emotion were labeled with the exact same Pleasure, Arousal and Dominance values. In reality not all animations with the same emotion express it with the same intensity, and the emotional coordinate values are subject to change even during the course of the same animation. It would be interesting to explore our approaches using an enriched dataset that further split each animation's labels into chunks, adding more granularity to the emotional expression of the data. Increasing the overall animation and emotional variety, alongside further tweaking our motion generation heuristic rules may also improve our system's performance on non-locomotion animations. It would also be worth exploring different avenues for LMA Feature generation. More specifically, we believe that Generative Adversarial Networks or Variational AutoEncoders could have the baseline generative capabilities to accomplish the feature generation task [16] and possibly outperform our own PAD to LMA mapping methodologies.

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