A Novel Approach to Analyzing Natural Child Body Gestures using Dominant Image Level Technique (DIL)

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Abstract— A novel approach to child body gesture is presented and discussed. The developed technique allows the monitoring and analysis of a child's behavior based on correlation between head, hand, and body poses. The DIL technique produces several organized maps resulting from image conversion and pixel redistribution, hence lumping individual gestures of the child and results in computable matrices, which is fed to an intelligent analysis system. The obtained results proved the technique to be capable of classifying child presented body pose with ability to model child's body gesture under various conditions.

Keywords— Head Gesture, Hand Gesture, Gesture-control, User interfaces, Image Conversion, Matrix Correlation, Classification.

I. INTRODUCTION

HUMAN tracking and gesture recognition is an interesting topic in the research for understanding human behavior, and for human-machine interaction and control. Humans naturally use gestures to convey responses. It is known that children can quickly learn to communicate through gestures before they learn to talk. Gestures are used instead of verbal communication to express various emotions. Using this process, human can interface with each other and with image-based computing machines. Human expressions using gestures are normally analyzed by converting them into sized understandable format. Body gesture is critical in most human-to-human conversational interaction; face pose is used to signal conversational turn-taking intent, offer explicit and implicit acknowledgement, and refer to specific objects of interest in the environment[1-5].

Human face is a rich source of nonverbal information. Indeed, not only it is provides identity information but it also presents ideas to understand social feelings and can be fundamental in revealing state of mind through social signals. Facial expressions form important part of human social interaction. Communication expresses ideas that are visualized in our minds by using words integrated with nonverbal behaviors. Hence, body language and verbal messages are used in complementary roles, to present clearer messages, where Face acts as a communication channel conveying the emotional content of our messages. In general, gestures such as eye and head movements, body movements, facial expressions and touch constitute the non- verbal message types of our body language.

Gesture recognition is an increasingly growing work area receiving, especially throughout the research fields of sign language recognition, security, human computer interaction, and intelligent cognitive systems. Human gesture is a spectrum that ranges from sign languages, through universal symbols, to natural and unconscious body moves. The ways of recognizing the gesture can be considered as a function of technology advancement. Progress of image processing technology has played an important role. Recent vision technique, video and web cam based gesture recognition has made it possible to capture any intuitive gesture for any ubiquitous devices from the natural environment.

Gesture recognition techniques focus mainly on recognition and classification issues, while examining closely pose localization and tracking, and on various feature extraction techniques of gesture modeling and related dynamical analysis, with computer vision, and pattern recognition implementations for feature extraction from image sequences. Classification schemes involve several methods such as neural networks, hidden Markov models, variants, principal component analysis, and many other machine learning methods or combinations of techniques [6-10].

In this paper a novel approach to child natural body gesture analysis is presented. The technique tracks several key Head, Hand and body landmarks, extract features that are used to classify the captured images into one of main emotional states like neutral, happy, and sad.

II. BACKGROUND

Emotions recognition in imaged data is an integral component in high-level computer vision applications such as interactive computing, and intelligence systems. Classification of human bodily expressions into emotional states is an important problem in computer vision. Extracting information is a continuous path from object recognition toward object

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understanding, enabling a flexible and interactive monitoring environment. Head and Hand actions coding, is a process by which judgment on emotional states is carried out based on actual movements which is an important component in building interactive image monitoring systems.

Child wellbeing relies on the ability of responsible people to maintain constant awareness of the child's environment as he lives and play. As children faces obstacles and reacts naturally in sometimes misunderstood way, the guardian must be aware of the change in behavior and be ready to react appropriately as he might not be present when the child's actions occur .

Although people have an astounding ability to cope with these changes, a guardian is fundamentally limited by what he can observe at any one time. When a guardian fails to notice a change in the child's behavior or the effect of new environment, there is an increased potential for an alarming change in course which subsequently will end in a collision. It is reasonable to assume that this danger could be mitigated if the guardian is notified when these situations arise using a novel image gesture technique presented in this work [11-15].

III. THE DIL TECHNIQUE

The presented system takes in image data. The output of the system is information regarding the detected emotion of the subject. This is accomplished using the developed DIL Technique using a Reference-Matching and Template-Matching methods. In this technique, each captured image is sorted into a specific matrix (IM_i, i=1, k) before all matrices are mapped into sequences , then the resulted sequences are then mapped into a final Matrix (IM_{final}) where the developed Roll and Slide algorithm is used to produce the classification row matrix (M_c). This is illustrated in equations 1-5:

$$IM_i = \begin{bmatrix} d_{11} & d_{12} & d_{13} & \dots & d_{1m} \\ d_{21} & d_{22} & d_{23} & \dots & d_{2m} \\ . & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & . \\ d_{n1} & d_{n2} & d_{n3} & \dots & d_{nm} \end{bmatrix} \dots(1)$$

$$IM_{final} = \begin{bmatrix} IM_{11} & IM_{12} & IM_{13} & \dots & IM_{1m} \\ IM_{21} & IM_{22} & IM_{23} & \dots & IM_{2m} \\ . & . & . & . & . \\ IM_{\mathrm{Re}f_1} & IM_{\mathrm{Re}f_2} & IM_{\mathrm{Re}f_3} & . & IM_{\mathrm{Re}f_m} \\ . & . & . & . & . \\ IM_{n1} & IM_{n2} & IM_{n3} & \dots & IM_{nm} \end{bmatrix} \dots(2)$$

$$Roll = \begin{bmatrix} R_{11} & R_{21} & 1 & \dots & R_{n1} \\ R_{12} & R_{22} & 1 & \dots & R_{n2} \\ .R_{13} & .R_{23} & 1 & . & R_{n3} \\ . & . & . & . & . \\ . & . & . & . & . \\ R_{1m} & R_{2m} & 1 & \dots & R_{nm} \end{bmatrix} \dots(3)$$

Where Rij: indicates the gesture and its average sequence value, so for example R11: gesture1 position1 (Fig. 2) and its average first sequence.

$$Slide = \begin{bmatrix} 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & \dots & 0 \\ . & . & . & \dots & . \\ . & . & . & \dots & . \\ (R_{1m}:1) & (R_{2m}:1) & 1 & \dots & (R_{nm}:1) \end{bmatrix} \dots(4)$$

The final mapping is expressed in equation (5).

$$M_c = [(C_1 \quad C_2 \quad 1 \quad \dots \quad C_n] \dots(5)$$

IV. RESULTS

Figures 1-7 demonstrate gestures by Dina Iskandarani used to test the algorithm, while Figures 8-14 show the mapped images sequences.

Fig.1: IM4:R41→R45-Neutral.


Fig.2: IM1:R11→R15-Happy1.


Fig.3: IM2:R21→R25-Happy2.


Fig.4: IM3:R31→R35-Happy3.


Fig.5: IM5:R51→R55-Sad1.


Fig.6: IM6:R61→R65-Sad2.


Fig.7: IM7:R71→R75-Sad3.

V. Analysis and Discussion

Visual gesture sequences tend to have distinct internal sub-structure and exhibit interesting dynamics between individual gestures [15-18]. This developed visual gesture recognition technique can capture both sub-gesture patterns and dynamics between gestures. Figures 8-12 show the averaged mapping sequences per image illustrations for a total of 7 gestures as follows:

1. Figure 8 represents the initial mapping where all gestures are discarded except for the neutral one as their weights are not sufficient to be recognized.

2. Figure 9 show that the used algorithm in the DIL technique starts acknowledging the presence of other emotional gestures beside the reference one, but with $Happy_1$ as the strongest in the Happy class and Sad_3 as the strongest in the sad class, with equal $Happy_2$ and $Happy_3$ values.

3. Figure10 presents the third mapping with better results as $Happy_2$ and $Happy_3$ show the strongest gestures and Sad_3 show the strongest gesture each in their respective classes.

4. Figure 11 show that $Happy_3$ and Sad_2 are the strongest emotional gestures each in their respective classes.

5. Figure 12 show that Sad_1 and Sad_2 are the only present gestures with equal values.

Based on previous figures and findings an automatic correlation (Slide algorithm) is carried out to produce plausible classification consistent with the captured images.

The result is shown in Figure 13.

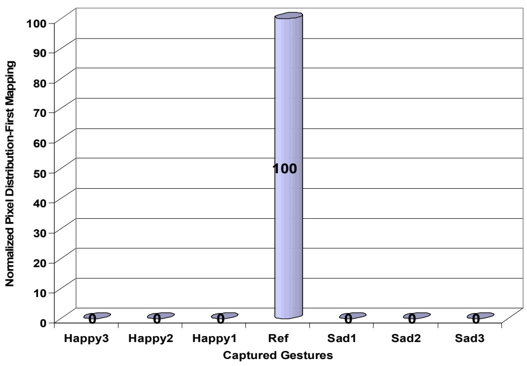

Fig.8: First Mapping of Gesture Images

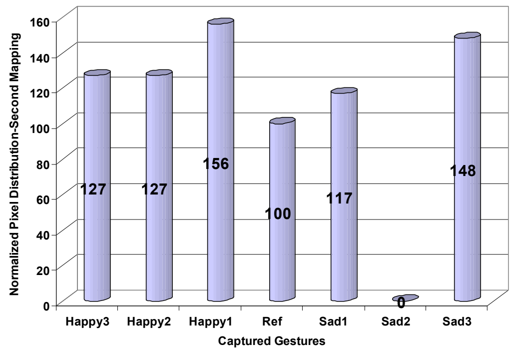

Fig.9: Second Mapping of Gesture Images

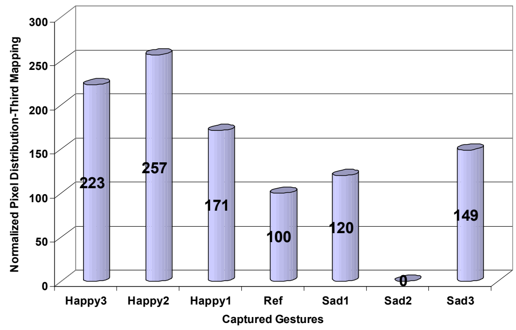

Fig.10: Third Mapping of Gesture Images

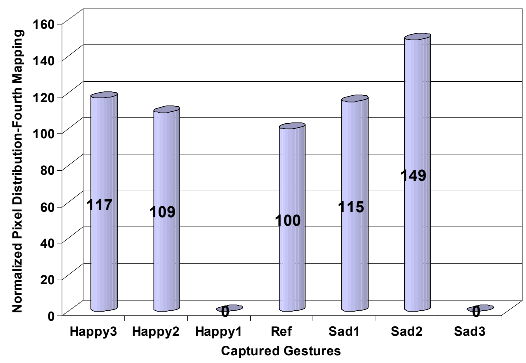

Fig.11: Fourth Mapping of Gesture Images

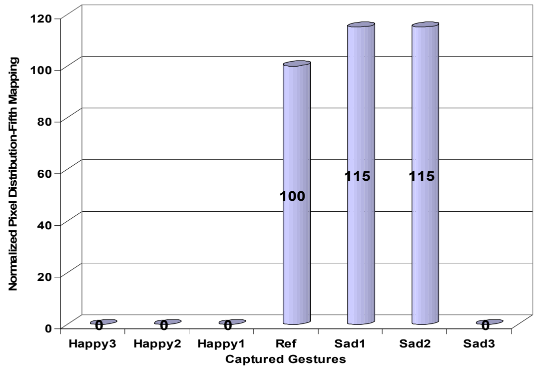

Fig.12: Fifth Mapping of Gesture Images

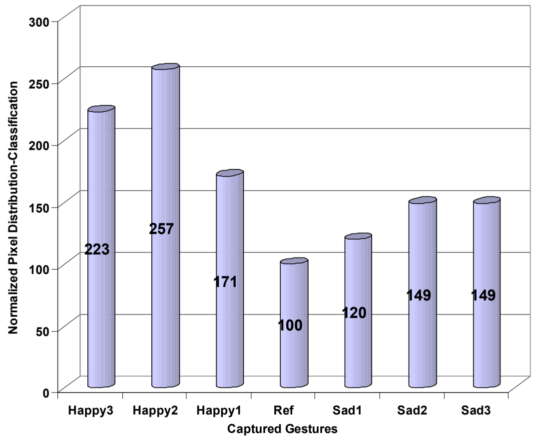

Fig.13: Mapping of Gesture Images-Classification.

From Figure 13 we realize that a correct classification and categorization is reached using the DIL technique with its Roll and Slide algorithms. In the classification figure, the results indicate two things:

1. Separation of different emotional gestures.

2. Correct classification of strength of emotional gestures, in this case {$Happy_2$, $Happy_3$} and {Sad_2, Sad_3} as the strongest emotions expressed by the child, with $Happy_2$ and either Sad_2 or Sad_3 are considered to be the strongest.

The closeness in results is due to the fact that the differences in presented gesture images per class are not that wide. However, if comparing Happy and Sad cases to each other we can see that there is a sizable difference in magnitude between them.

The used mapping with Roll and Slide algorithm is illustrated in matrices 6-18 where:

IM1:R11→R15-$Happy_1$.
IM2:R21→R25-$Happy_2$.
IM3:R31→R35-$Happy_3$.
IM4:R41→R45-Reference (Neutral).
IM5:R51→R55-Sad_1.
IM6:R61→R66-Sad_2.
IM7:R71→R75-Sad_3.

- Final Image Matrix:

$$IM_{final} = \begin{bmatrix} 248734 & 138978 & 154321 & 670481 & 274338 & 252092 & 385583 \\ 1526795 & 1236159 & 1217805 & 966078 & 1116783 & 957993 & 1452444 \\ 376867 & 555248 & 476937 & 217166 & 256361 & 182471 & 324316 \\ 694973 & 938112 & 1023982 & 871471 & 985819 & 1308709 & 722314 \\ 284427 & 224644 & 178114 & 360530 & 412695 & 421267 & 236693 \end{bmatrix} \quad ...(6)$$

- Optimized Final Image Matrix:

$$OIM_{final} = \begin{bmatrix} 0.080 & 0.044 & 0.051 & 0.217 & 0.090 & 0.081 & 0.124 \\ 0.490 & 0.400 & 0.400 & 0.314 & 0.367 & 0.307 & 0.465 \\ 0.120 & 0.180 & 0.156 & 0.070 & 0.084 & 0.058 & 0.104 \\ 0.220 & 0.303 & 0.335 & 0.282 & 0.324 & 0.419 & 0.231 \\ 0.090 & 0.073 & 0.058 & 0.117 & 0.135 & 0.135 & 0.076 \end{bmatrix} \quad ...(7)$$

- Normalized Final Image Matrix:

$$NIM_{final} = \begin{bmatrix} 0.37 & 0.20 & 0.24 & 1.00 & 0.41 & 0.37 & 0.57 \\ 1.56 & 1.27 & 1.27 & 1.00 & 1.17 & 0.98 & 1.48 \\ 1.71 & 2.57 & 2.23 & 1.00 & 1.2 & 0.83 & 1.49 \\ 0.78 & 1.07 & 1.19 & 1.00 & 1.15 & 1.49 & 0.82 \\ 0.77 & 0.62 & 0.5 & 1.00 & 1.15 & 1.15 & 0.65 \end{bmatrix} \quad ...(8)$$

- Roll and Slide algorithm:

$$Roll_1 = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 1.00 & 0.00 & 0.00 & 0.00 \\ 1.56 & 1.27 & 1.27 & 1.00 & 1.17 & 0.98 & 1.48 \\ 1.71 & 2.57 & 2.23 & 1.00 & 1.2 & 0.83 & 1.49 \\ 0.78 & 1.07 & 1.19 & 1.00 & 1.15 & 1.49 & 0.82 \\ 0.77 & 0.62 & 0.5 & 1.00 & 1.15 & 1.15 & 0.65 \end{bmatrix} \quad ...(9)$$

$$Roll_2 = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 1.00 & 0.00 & 0.00 & 0.00 \\ 1.56 & 1.27 & 1.27 & 1.00 & 1.17 & 0.00 & 1.48 \\ 1.71 & 2.57 & 2.23 & 1.00 & 1.2 & 0.83 & 1.49 \\ 0.78 & 1.07 & 1.19 & 1.00 & 1.15 & 1.49 & 0.82 \\ 0.77 & 0.62 & 0.5 & 1.00 & 1.15 & 1.15 & 0.65 \end{bmatrix} \quad ...(10)$$

$$Roll_3 = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 1.00 & 0.00 & 0.00 & 0.00 \\ 1.56 & 1.27 & 1.27 & 1.00 & 1.17 & 0.00 & 1.48 \\ 1.71 & 2.57 & 2.23 & 1.00 & 1.2 & 0.00 & 1.49 \\ 0.78 & 1.07 & 1.19 & 1.00 & 1.15 & 1.49 & 0.82 \\ 0.77 & 0.62 & 0.5 & 1.00 & 1.15 & 1.15 & 0.65 \end{bmatrix} \quad ...(11)$$

$$Roll_4 = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 1.00 & 0.00 & 0.00 & 0.00 \\ 1.56 & 1.27 & 1.27 & 1.00 & 1.17 & 0.00 & 1.48 \\ 1.71 & 2.57 & 2.23 & 1.00 & 1.2 & 0.00 & 1.49 \\ 0.00 & 1.07 & 1.19 & 1.00 & 1.15 & 1.49 & 0.00 \\ 0.77 & 0.62 & 0.5 & 1.00 & 1.15 & 1.15 & 0.65 \end{bmatrix} \quad ...(12)$$

$$Roll_5 = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 1.00 & 0.00 & 0.00 & 0.00 \\ 1.56 & 1.27 & 1.27 & 1.00 & 1.17 & 0.00 & 1.48 \\ 1.71 & 2.57 & 2.23 & 1.00 & 1.2 & 0.00 & 1.49 \\ 0.00 & 1.07 & 1.19 & 1.00 & 1.15 & 1.49 & 0.00 \\ 0.00 & 0.00 & 0.00 & 1.00 & 1.15 & 1.15 & 0.00 \end{bmatrix} \quad ...(13)$$

$$Slide_1 = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 1.56 & 1.27 & 1.27 & 1.00 & 1.17 & 0.00 & 1.48 \\ 1.71 & 2.57 & 2.23 & 1.00 & 1.2 & 0.00 & 1.49 \\ 0.00 & 1.07 & 1.19 & 1.00 & 1.15 & 1.49 & 0.00 \\ 0.00 & 0.00 & 0.00 & 1.00 & 1.15 & 1.15 & 0.00 \end{bmatrix} ...(14)$$

$$Slide_2 = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 1.71 & 2.57 & 2.23 & 1.00 & 1.2 & 0.00 & 1.49 \\ 0.00 & 1.07 & 1.19 & 1.00 & 1.15 & 1.49 & 0.00 \\ 0.00 & 0.00 & 0.00 & 1.00 & 1.15 & 1.15 & 0.00 \end{bmatrix} ...(15)$$

$$Slide_3 = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 1.71 & 2.57 & 2.23 & 1.00 & 1.2 & 1.49 & 1.49 \\ 0.00 & 0.00 & 0.00 & 1.00 & 1.15 & 1.15 & 0.00 \end{bmatrix} ...(16)$$

$$Slide_4 = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 1.71 & 2.57 & 2.23 & 1.00 & 1.20 & 1.49 & 1.49 \end{bmatrix} ...(17)$$

$$M_c = \begin{bmatrix} 1.71 & 2.57 & 2.23 & 1.00 & 1.20 & 1.49 & 1.49 \end{bmatrix} ..(18)$$

In real life cases, it is desired to have a decision regarding the mental status of a child being happy or sad. To achieve this, a reduced normalized image matrix is used before the application of the DIL technique. The resulted classification is show in matrices 19-29 and Figure 14.

- Reduced Normalized Final Image Matrix:

$$RNIM_{final} = \begin{bmatrix} 0.27 & 1 & 0.45 \\ 1.37 & 1 & 1.21 \\ 2.17 & 1 & 1.17 \\ 1.01 & 1 & 1.15 \\ 0.63 & 1 & 0.98 \end{bmatrix} ...(19)$$

- Roll and Slide algorithm:

$$Roll_1 = \begin{bmatrix} 0 & 1 & 0 \\ 1.37 & 1 & 1.21 \\ 2.17 & 1 & 1.17 \\ 1.01 & 1 & 1.15 \\ 0.63 & 1 & 0.98 \end{bmatrix} ...(20)$$

$$Roll_2 = \begin{bmatrix} 0 & 1 & 0 \\ 1.37 & 1 & 1.21 \\ 2.17 & 1 & 1.17 \\ 1.01 & 1 & 1.15 \\ 0.63 & 1 & 0.98 \end{bmatrix} ...(21)$$

$$Roll_3 = \begin{bmatrix} 0 & 1 & 0 \\ 1.37 & 1 & 1.21 \\ 2.17 & 1 & 1.17 \\ 1.01 & 1 & 1.15 \\ 0.63 & 1 & 0.98 \end{bmatrix} ...(22)$$

$$Roll_4 = \begin{bmatrix} 0 & 1 & 0 \\ 1.37 & 1 & 1.21 \\ 2.17 & 1 & 1.17 \\ 1.01 & 1 & 1.15 \\ 0.63 & 1 & 0.98 \end{bmatrix} ...(23)$$

$$Roll_5 = \begin{bmatrix} 0 & 1 & 0 \\ 1.37 & 1 & 1.21 \\ 2.17 & 1 & 1.17 \\ 1.01 & 1 & 1.15 \\ 0 & 1 & 0 \end{bmatrix} ...(24)$$

$$Slide_1 = \begin{bmatrix} 0 & 1 & 0 \\ 1.37 & 1 & 1.21 \\ 2.17 & 1 & 1.17 \\ 1.01 & 1 & 1.15 \\ 0 & 1 & 0 \end{bmatrix} ...(25)$$

$$Slide_2 = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 2.17 & 1 & 1.21 \\ 1.01 & 1 & 1.15 \\ 0 & 1 & 0 \end{bmatrix} ...(26)$$

$$Slide_3 = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 2.17 & 1 & 1.21 \\ 0 & 1 & 0 \end{bmatrix} ...(27)$$

$$Slide_4 = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 2.17 & 1 & 1.21 \end{bmatrix} \ldots(28)$$

- Classification Row Matrix:

$$M_c = [2.17 \quad 1 \quad 1.21] \ldots(29)$$

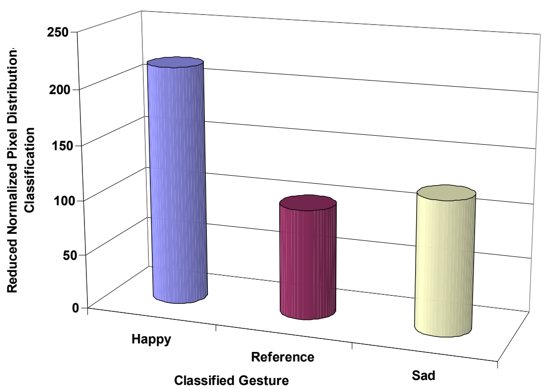

Fig.14: General Mapping of Gesture Images.

Taking into account that the child's gesture will not be known in advance, this means that the substituted values in the matrix regarding type of movement will not be known in advance hence, the rows in equation (2) could be arranged both in terms of action and its instance of occurrence in a number of ways according to which sequence of actions have taken place which can follow different scenarios and can be represented by a probability function of matrix elements arrangements of captured gestures. However, the sequence of events is associated with stored captured image in a database which in turn preserves the integrity of the classification and prediction system.

From the obtained results, a relationship is realized between the reference image and any performed gesture:

$$gesture_1 = f_1(reference)\ldots(30)$$

$$gesture_2 = f_2(reference) = f_2^{-1}(gesture_1)\ldots(31)$$

- **Class α (Happy):**

$$gesture_i = f_i(reference) = f_i^{-1}(gesture_{i-1})\ldots(32)$$

- **Class β (Sad):**

$$gesture_j = f_j(reference) = f_j^{-1}(gesture_{j-1})\ldots(33)$$

- **Any class γ:**

$$gesture_k = f_k(reference) = f_k^{-1}(gesture_{k-1})\ldots(34)$$

- **Sequences originating from the reference gesture:**

$$gesture_1 = f_1(reference)\ldots(35)$$

$$gesture_2 = f_2(reference) = f_2(gesture_1)\ldots(36)$$

- **Intermixed sequences of gestures departing from the reference gesture:**

$$gesture_m = f_m(probability(gesture_i, gesture_j, \ldots, gesture_k))\ldots(37)$$

$$gesture_n = f_n(gesture_m)\ldots(38)$$

For the presented case, the combinational possibilities and scenario probabilities can be detailed, for example, one set of gestures {Reference, Happy1, Happy2, Happy3, Sad1, Sad2, Sad3} as in matrices P_i, P_j, and P_k:

$$P_i = \begin{bmatrix} x & x & x & x & x & x & x \\ x & x & x & x & x & x & x \\ x & x & x & x & x & x & x \\ h_1 & h_2 & h_3 & ref & s_1 & s_2 & s_3 \\ x & x & x & x & x & x & x \\ x & x & x & x & x & x & x \\ x & x & x & x & x & x & x \end{bmatrix} \ldots(39)$$

$$P_j = \begin{bmatrix} ref & h_1 & h_2 & h_3 & s_1 & s_2 & s_3 \\ h_1 & ref & h_2 & h_3 & s_1 & s_2 & s_3 \\ h_1 & h_2 & ref & h_3 & s_1 & s_2 & s_3 \\ x & x & x & x & x & x & x \\ h_1 & h_2 & h_3 & s_1 & ref & s_2 & s_3 \\ h_1 & h_2 & h_3 & s_1 & s_2 & ref & s_3 \\ h_1 & h_2 & h_3 & s_1 & s_2 & s_3 & ref \end{bmatrix} \ldots(40)$$

$$P_k = \begin{bmatrix} ref & h_1 & h_2 & h_3 & x & x & x \\ h_1 & ref & h_2 & h_3 & x & x & x \\ h_1 & h_2 & ref & h_3 & x & x & x \\ x & x & x & x & x & x & x \\ x & x & x & s_1 & ref & s_2 & s_3 \\ x & x & x & s_1 & s_2 & ref & s_3 \\ x & x & x & s_1 & s_2 & s_3 & ref \end{bmatrix} \ldots(41)$$

Matrices (39), (40), and (41) show:

1. Discrete uncorrelated types of gestures {Happy, Sad} but filtered into either side of the reference gesture shown in matrix p_i and Figure 15.

2. Continuous correlated gestures shown in matrix p_j and Figure 16.

3. Discrete but correlated gestures each filtered class is internally correlated shown in matrix p_k and Figure 17.

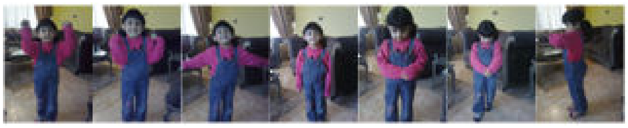

Fig.15: Probable gesture sequence p_i for one possible set.

Fig.16: Probable gesture sequence (first & last) p_j for one possible set.

Fig.17: Probable gesture sequence p_k (first & Last) for one possible set.

By closely examining each probability matrix group per set, it is realized that a relationship exists between the Happy and Sad gestures through the reference (neutral) gesture represented in equations 42-43:

$$gesture\,(happy) = \xi\ gesture\,(sad) \ldots(42)$$

$$gesture\,(ref, causal\ change) = \xi\, gesture\,(ref, causal\ change) \ldots(43)$$

The Optimum Operations Size (OOS) for Roll-Slide follow the rule in equation (44) below.

$$OOS = (N-1)(M-1) \ldots (44)$$

N: number of sequences per image
M: number of gestures

Table 1 show the effect of the number of performed gestures and number of sequences per gesture that can lead to a correct classification on the overall operational size. This is important in terms of measuring the efficiency of the developed algorithm. It also show by means of symmetry cancellation the optimum number of operations per recommended maximum number of sequences per image for a given number of gestures, While Figure 18 illustrate such selection curve.

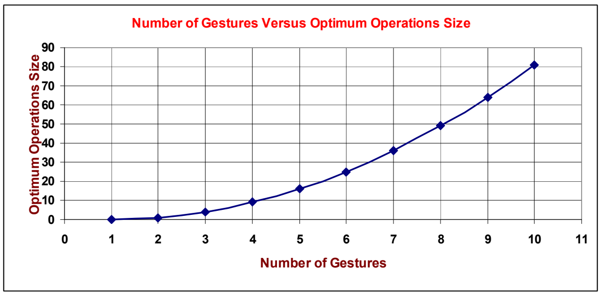

Fig. 18: Relationship between Gestures and Operations Size.

M	N=2	N=3	N=4	N=5	N=6	N=7	N=8	N=9	N=10
1	0	0	0	0	0	0	0	0	0
2	1	2	3	4	5	6	7	8	9
3	2	4	6	8	10	12	14	16	18
4	3	6	9	12	15	18	21	24	27
5	4	8	12	16	20	24	28	32	36
6	5	10	15	20	25	30	35	40	45
7	6	12	18	24	30	36	42	48	54
8	7	14	21	28	35	42	49	56	63
9	8	16	24	32	40	48	56	64	72
10	9	18	27	36	45	54	63	72	81

Table 1: Optimizing number of image sequences for a given number of gestures

It is clear from the table that the maximum number of sequences is equal to the number of gestures. This indicates that each gesture has a unique sequence level that classifies it within a predetermined number of sequences in a converted image matrix. In addition, the plotted curve follows a power law.

VI. COCLUSIONS

The presented new system efficiently detects and classifies body gestures, and treats the image as a lumped component to analyze child mode and behavior. It is truly inexpensive, since only a common computer with a cheap webcam is needed, with no need for any kind of environmental setup and calibration.

The classification row matrix clearly discriminate between different gestures and is stored in a database that correlate gesture images to matrix values for future classification

In order to observe record and analyze the characteristics of human gestures and to verify and evaluate the developed algorithm and its application system, the gesture database is systematically constructed.

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