Application of General Type-2 Fuzzy Set in Emotion Recognition from Facial Expression

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Abstract. This paper proposes a new technique for emotion recognition of an unknown subject using General Type-2 Fuzzy sets (GT2FS). The proposed technique includes two steps- first, a type-2 fuzzy face-space is created with the background knowledge of facial features of different subjects containing different emotions. Second, the emotion of an unknown facial expression is determined based on the consensus of the measured facial features with the fuzzy face-space. The GT2FS has been used here to model the fuzzy face space. The general type-2 fuzzy involves both primary and secondary membership distributions which have been obtained here by formulating and solving an optimization problem. The optimization problem here attempts to minimize the difference between two decoded signals: the first one being the type-1 defuzzification of the average primary membership distributions obtained from n-subjects, while the second one refers to the type-2 defuzzified signal for a given primary distribution with secondary memberships as unknown. The uncertainty management policy adopted using general type-2 fuzzy set has resulted in a classification accuracy of 96.67%.

Keywords: Emotion Recognition, Facial feature extraction, Type-2 primary membership, Type-2 secondary membership, Fuzzy Face Space.

1 Introduction

Emotion recognition is currently gaining importance for its increasing scope of applications in human-computer interactive systems. Several modalities of emotion recognition, including facial expression, voice, gesture and posture have been studied in the literature. However, irrespective of the modality, emotion recognition comprises two fundamental steps involving feature extraction and classification. Feature extraction refers to determining a set of features/attributes, preferably independent, which together represents a given emotional expression. Classification aims at mapping emotional features into one of several emotion classes.

B.K. Panigrahi et al. (Eds.): SEMCCO 2011, Part I, LNCS 7076, pp. 460–468, 2011.

Among the well-known methods of determining human emotions, Fourier descriptor [1], template matching [2], and neural network techniques [3], [4] deserve special mention. Other important works undertaken so far for recognition of emotions from facial expression by selecting suitable features include [5], [6], [7] and by identifying the right classifier include [3], [4],[10].

The paper provides an alternative approach to emotion recognition from an unknown facial expression, when the emotion class of individual facial expression of a large number of experimental subjects is available. The General Type-2 fuzzy set (GT2FS) based approach employs to construct a fuzzy face space, comprising both primary and secondary membership distributions, obtained from known facial expressions of several subjects containing multiple instances of the same emotion for each subject. The emotion class of an unknown facial expression is determined by obtaining maximum support of each class to the given facial expression. The class with the maximum support is the winner. The maximum support evaluation here employs both primary and secondary distributions. Experiments reveal that the classification accuracy of emotion of an unknown person by the GT2FS based scheme is as high as 96%.

The paper is divided into five sections. In section 2, we propose the principle of GT2FS approach. Methodology of the proposed scheme is discussed in section 3. Experimental details are given in section 4. Conclusions are listed in section 5.

2 Principles Used in the GT2FS Approach

The GT2FS based reasoning realized with measurements taken from n-subjects, requires $k \times m \times n$ general type-2 fuzzy sets to determine the emotion class of an unknown facial expression where, k is the number of emotion classes and m is the number of features.

Let $F=\{f_1, f_2, \ldots, f_m\}$ be the set of m facial features. Let $\mu_{\tilde{A}}(f_i)$ be the primary membership in [0,1] of the feature f_i to be a member of set $\tilde{A}$, and $\mu(f_i, \mu_{\tilde{A}}(f_i))$ be the secondary membership of the measured variable f_i in [0,1]. If the measurement of a facial feature, f_i, is performed p times on the same subject experiencing the same emotion, and the measurements are quantized into q intervals of equal size, we can evaluate the frequency of occurrence of the measured variable f_i in q quantized intervals. The interval containing the highest frequency of occurrence then can be identified, and its centre, m_i, approximately represents the mode of the measurement variable f_i. The second moment, σ_i, around m_i is determined, and an exponential bell-shaped (Gaussian) membership function centered on m_i and with a spread σ_i is used to represent the membership function of the random variable f_i. This function represents the membership of f_i to be CLOSE-TO the central value, m_i. It may be noted that a bell-shaped (Gaussian-like) membership curve would have a peak at the centre with a membership value one, indicating that membership at this point is the largest for an obvious reason of having the highest frequency of f_i at the centre.

On repetition of the above experiment for variable f_i on n subjects, each experiencing the same emotion, we obtain n such membership functions, each one for one individual subject. Naturally, the measurement variable f_i now has both intra- and inter-personal level uncertainty. The intra-level uncertainty occurs due to the pre-assumption of the bell-shape (Gaussian distribution) of the primary membership function, and the inter-level uncertainty occurs due to multiplicity of the membership distribution for n subjects. Thus a new measurement for an unknown facial expression can be encoded using all the n-membership curves, giving n possible membership values, thereby giving rise to uncertainty in the fuzzy space.

GT2FS approach tunes the primary membership values for the given measurements using the secondary memberships of the same measurement, and thus reduces the degree of intra-level uncertainty of the primary distributions. The reduction in the degree of uncertainty helps in improving the classification accuracy of emotion at the cost of additional complexity required to evaluate type-2 secondary distributions and also to reason with k × m × n fuzzy sets.

Let $fi^{/}$ be the measurement of the i-th feature for an unknown subject. Now, by consulting the n primary membership distributions obtained from n-subjects for a given emotion, we obtain n primary membership values for the measurement $f_i^{/}$ given by $\mu_{\tilde{A}}^{1}(f_i^{/}), \mu_{\tilde{A}}^{2}(f_i^{/}), \ldots\ldots, \mu_{\tilde{A}}^{n}(f_i^{/})$. Let the secondary membership values for each primary membership respectively be $\mu(f_i^{/}, \mu_{\tilde{A}}^{1}(f_i^{/})), \mu(f_i^{/}, \mu_{\tilde{A}}^{2}(f_i^{/})), \ldots\ldots, \mu(f_i^{/}, \mu_{\tilde{A}}^{n}(f_i^{/}))$. Since the secondary memberships denote the degree of accuracy of the primary memberships, the uncertainty in a primary membership distribution can be reduced by multiplying each primary membership value by its secondary membership. Thus the modified primary membership values are given by

$$\left.\begin{aligned} {}^{\mathrm{mod}}\mu_{\tilde{A}}^{1}(f_i^{/}) &= \mu_{\tilde{A}}^{1}(f_i^{/}) \times \mu(f_i^{/}, \mu_{\tilde{A}}^{1}(f_i^{/})), \\ {}^{\mathrm{mod}}\mu_{\tilde{A}}^{2}(f_i^{/}) &= \mu_{\tilde{A}}^{2}(f_i^{/}) \times \mu(f_i^{/}, \mu_{\tilde{A}}^{2}(f_i^{/})), \\ &\cdots\cdots\cdots\cdots\cdots\cdots \\ {}^{\mathrm{mod}}\mu_{\tilde{A}}^{n}(f_i^{/}) &= \mu_{\tilde{A}}^{n}(f_i^{/}) \times \mu(f_i^{/}, \mu_{\tilde{A}}^{n}(f_i^{/})) \end{aligned}\right\} \tag{1}$$

where ${}^{\mathrm{mod}}\mu_{\tilde{A}}^{j}(f_i^{/})$ denotes the modified primary membership value for j-th subject. The next step is to determine the range of ${}^{\mathrm{mod}}\mu_{\tilde{A}}^{j}(f_i^{/})$ for j= 1 to n, comprising the minimum and the maximum given by $[{}^{\mathrm{mod}}\underline{\mu}_{\tilde{A}}(f_i^{/}), {}^{\mathrm{mod}}\overline{\mu}_{\tilde{A}}(f_i^{/})]$, where

$${}^{\mathrm{mod}}\underline{\mu}_{\tilde{A}}(f_i^{/}) = Min\ \{{}^{\mathrm{mod}}\mu_{\tilde{A}}^{1}(f_i^{/}), {}^{\mathrm{mod}}\mu_{\tilde{A}}^{2}(f_i^{/}), \ldots, {}^{\mathrm{mod}}\mu_{\tilde{A}}^{n}(f_i^{/})\},$$

$${}^{\mathrm{mod}}\overline{\mu}_{\tilde{A}}(f_i^{/}) = Max\ \{{}^{\mathrm{mod}}\mu_{\tilde{A}}^{1}(f_i^{/}), {}^{\mathrm{mod}}\mu_{\tilde{A}}^{2}(f_i^{/}), \ldots, {}^{\mathrm{mod}}\mu_{\tilde{A}}^{n}(f_i^{/})\},$$

If there exist m different facial features, then for each feature we would have such an interval, and consequently we obtain m such intervals given by

$$[{}^{\mathrm{mod}}\underline{\mu}_{\tilde{A}}(f_1^{/}), {}^{\mathrm{mod}}\overline{\mu}_{\tilde{A}}(f_1^{/})], [{}^{\mathrm{mod}}\underline{\mu}_{\tilde{A}}(f_2^{/}), {}^{\mathrm{mod}}\overline{\mu}_{\tilde{A}}(f_2^{/})], \ldots [{}^{\mathrm{mod}}\underline{\mu}_{\tilde{A}}(f_m^{/}), {}^{\mathrm{mod}}\overline{\mu}_{\tilde{A}}(f_m^{/})]$$

The proposed reasoning system employs a particular format of rules, commonly used in fuzzy classification problems. Consider for instance a fuzzy rule, given by

R_c: if f_1 is $\tilde{A}_1$ AND f_2 is $\tilde{A}_2$ …. AND f_m is $\tilde{A}_m$ then emotion class is c.

Here, f_i for i=1 to m are m-measurements (feature value) in the general type-2 fuzzy sets $\tilde{A}_1$, $\tilde{A}_2$, …, $\tilde{A}_m$ respectively, given by

$$\tilde{A}_i = [\underline{\mu}_{\tilde{A}}(f_i), \overline{\mu}_{\tilde{A}}(f_i)], \forall i \cdot \tag{2}$$

Since an emotion is characterized by all of these m features, to find the overall support of the m features (m measurements made for the unknown subject) to the emotion class c represented by the n primary memberships, we use the fuzzy meet operation

$$S_c^{\min} = Min\{^{\mathrm{mod}}\underline{\mu}_{\tilde{A}}(f_1^{/}), ^{\mathrm{mod}}\underline{\mu}_{\tilde{A}}(f_2^{/}), ..., ^{\mathrm{mod}}\underline{\mu}_{\tilde{A}}(f_m^{/}), \} \tag{3}$$

$$S_c^{\max} = Min\{^{\mathrm{mod}}\overline{\mu}_{\tilde{A}}(f_1^{/}), ^{\mathrm{mod}}\overline{\mu}_{\tilde{A}}(f_2^{/}), ..., ^{\mathrm{mod}}\overline{\mu}_{\tilde{A}}(f_m^{/})\} \tag{4}$$

Thus we can say that the unknown subject is experiencing the emotion class c at least to the extent s_c^{min}, and at most to the extent s_c^{max}.

To reduce the non-specificity associated with the interval S_{c-i}, the most conservative approach would be to use lower bound, while the most liberal view would to use the upper bound of the interval as the support for the class c. In absence of any additional information, a balanced approach would be to use center of the interval as the support for the class c by the n primary memberships to the unknown subject [8]. We compute the centre, S_c of the interval S_{c-i}.Thus S_c is the degree of support that the unknown facial expression is in emotion class *c*.

$$S_c = (s_c^{min} + s_c^{max})/2. \tag{5}$$

Now to predict the emotion of a person from his facial expression, we determine S_c for each emotion class. Presuming that there exist k emotion classes, let us denote them by S_1, S_2,…., S_k for emotion class *1, 2,…, k*, respectively. Since a given facial expression may convey different emotions with different degrees, we resolve the conflict by ranking the S_i for $i = 1$ *to k*, and thus determine the emotion class r, for which $S_r >= S_i$ for all *i* following the Rule R_c.

To make the algorithm robust, we consider association of fuzzy encoded measurements with emotion class by considering the weakest reliability of the joint occurrence of the fuzzy measurements, and identify the winning emotion class having this measure of reliability superseding the same of other emotion classes.

3 Methodology

We now briefly discuss the main steps involved in fuzzy face space construction based on the measurements of m facial features for n-subjects, each having *l* instances of facial expression for a particular emotion. We need to classify a facial expression of an unknown person into one of k emotion classes.

1. We extract m facial features for n subjects, each having *l* instances of facial expression for a particular emotion. The above features are extracted for k-emotion classes.
2. We construct a fuzzy face space for each emotion class separately. The fuzzy face space for an emotion class comprises a set of n primary membership and secondary membership distributions for each feature. Thus we have m groups of n-primary as well as secondary membership distributions. Each membership curve is constructed from *l*-facial instances of a subject attempted to exhibit a particular emotion in her facial expression by acting.
3. For a given feature $f_i^{/}$, we consult each primary and secondary membership curve under a given emotion class, and take the product of primary and secondary membership at $f_i= f_i^{/}$. The resulting membership value obtained for the membership curves for the subject w is given by

$$^{\text{mod}}\mu_{\tilde{A}}^{w}(f_i^{/}) = \mu_{\tilde{A}}^{w}(f_i^{/}) \times \mu(f_i^{/}, \mu_{\tilde{A}}^{w}(f_i^{/})) \tag{6}$$

   Now, for w = 1 to n, we evaluate $^{\text{mod}}\mu_{\tilde{A}}^{w}(f_i^{/})$, and thus obtain the minimum and the maximum values of $^{\text{mod}}\mu_{\tilde{A}}^{w}(f_i^{/})$, to obtain a range of uncertainty $[^{\text{mod}}\underline{\mu}_{\tilde{A}}(f_i^{/}), {}^{\text{mod}}\overline{\mu}_{\tilde{A}}(f_i^{/})]$. This is repeated for all features under each emotion class.
4. Now for an emotion class j, we take fuzzy meet operation over the ranges for each feature to evaluate the range of uncertainty for individual emotion class. The meet operation here is computed by taking cumulative t-norm of $^{\text{mod}}\underline{\mu}_{\tilde{A}}(f_i^{/})$ and $^{\text{mod}}\overline{\mu}_{\tilde{A}}(f_i^{/})$ separately for i= 1 to m, and thus obtaining S_j^{min} and S_j^{max} respectively.
5. The support of the j-th emotion class to the measurements is evaluated by taking average of S_j^{min} and S_j^{max}, and defining the result by S_j.
6. Now by using classifier rule, we determine the maximum support offered by all the k emotion classes, and declare the unknown facial expression to have emotion r, if $S_r > S_i$ for all emotion class *i= 1 to k.*

4 Experimental Details

In this section, we present the experimental details of emotion recognition using the principles introduced in section 2 and 3. We here consider 5 emotion classes, (i.e., k=5) including anger, fear, disgust, happiness and relaxation. The experiment is conducted with two sets of subjects: a) the first set of n (=10) subjects is considered for designing the fuzzy face-space and, b) the other set of 30 facial expressions taken from 6 unknown subjects are considered to validate the result of the proposed emotion classification scheme. Five facial features, (i.e., m=5) have been used here to design the type-2 fuzzy face-space. We now briefly outline the main steps.

4.1 Feature Extraction

Feature extraction is a fundamental step in emotion recognition. Existing research results [9],[10] reveal that the most important facial regions responsible for the manifestation of emotion are the eyes and the lips. This motivated us to select the following features: Left Eye Opening (EO_L), Right Eye Opening (EO_R), Distance between the Lower Eyelid to the Eyebrow for the Left Eye (LEE_L), Distance between the Lower Eyelid to Eyebrow for the Right Eye (LEE_R), and the Maximum Mouth opening (MO) including the lower and the upper lips. Fig. 1 explains the above facial features on a selected facial image.

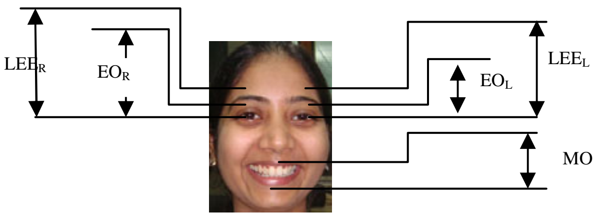

Fig. 1. Facial Features

4.2 Creating the Type-2 Fuzzy Face-Space

The Type-2 fuzzy face-space contains the primary and corresponding secondary membership distributions for each facial feature. Since we have 5 facial features and the experiment includes 5 distinct emotions of 10 subjects, we obtain 10×5×5=250 primary as well as secondary membership curves. To compute primary memberships, 10 instances of a given emotion is used. These 250 membership curves are grouped into 25 heads, each containing 10 membership curves of ten subjects for a specific feature for a given emotion. Fig. 2. (a) gives an illustration of one such group of 10 membership distributions for the feature EO_L for the emotion: disgust.

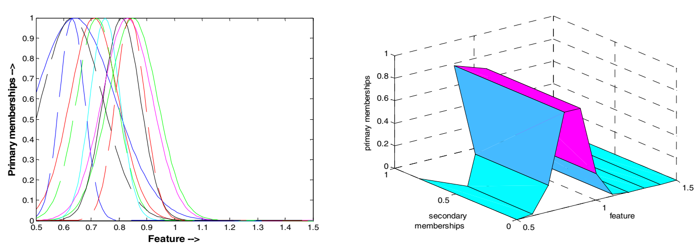

Fig. 2. (a). Membership distributions for emotion disgust and feature EO_L (b) Secondary Membership curve of Subject1

For each primary membership distribution, we have a corresponding secondary membership distribution. Thus we obtain 250 secondary membership distributions. One illustrative type-2 secondary distributions of subject 1 for the feature EO_L for the emotion disgust are given in Fig. 2. (b) The axes in the figure represent feature (EO_L), primary and secondary membership values as indicated.

4.3 Emotion Recognition of an Unknown Facial Expression

The emotion recognition problem addressed here attempts to determine the emotion of an unknown person from her facial expression. To keep the measurements in an emotional expression normalized and free from distance variation from the camera focal plane, we construct a bounding box, covering only the face region, and the reciprocal of the diagonal of the bounding box is used as a scale factor for normalization of the measurements. The normalized features obtained from Fig.3 are enlisted in Table 1. We now briefly explain the experimental results obtained by our proposed method.

Fig. 3. Facial Image of an unknown subject

Table 1. Extracted Features of Fig. 3

EO_L	EO_R	MO	LEE_L	LEE_R
0.026	0.026	0.135	0.115	0.115

The GT2FS based recognition scheme considers a fuzzy face space of 5 sets of 10 primary membership distributions as in Fig. 2 (a), and the corresponding secondary membership distributions to the individual primary membership distribution of 5 features obtained from facial expressions carrying 5 distinct emotions for 10 different subjects are determined using curves like Fig. 2 (b).

Table 2. Calculated Type-2 Membership Values For Feature :EO_L, Emotion: Disgust

Feature	Primary Memberships (μ_{pri})	Secondary memberships (μ_{sec})	$\mu^{mod}=\mu_{pri} \times \mu_{sec}$	Range (min{ μ^{mod}},max{ μ^{mod} })
EO_L	0.65	0.72	0.468	0.044-0.468
	0.10	0.55	0.055	
	0.15	0.58	0.087	
	0.45	0.68	0.306	
	0.18	0.56	0.1008	
	0.55	0.68	0.374	
	0.08	0.55	0.044	
	0.41	0.63	0.2583	
	0.16	0.53	0.0848	
	0.12	0.59	0.0708	

Table 3. Calculated Feature Ranges and Centre Value For Each Emotion

Emotion	Range of Secondary Membership for Features					Range S_c^j after fuzzy Meet operation (**centre**)
	EO_L	EO_R	MO	LEE_L	LEE_R	
Anger	0-0.14	0 - 0.17	0.39-0.964	0.0034-0.814	0.0029-0.781	0-0.14(0.07)
Disgust	0.044-0.468	0.041-0.531	0-0	0-0.39	0.-0.283	0-0(0)
Fear	0 - 0.298	0-0.275	0.04-0.742	0.054-0.473	0.057-0.511	0-0.275(0.1375)
Happy	0 - 0.555	0-0.604	0.573-0.910	0.133-0.851	0.3214-0.7213	0-0.555(**0.2775**)
Relaxed	0 - 0.132	0-0.221	0-0	0.013-0.458	0.046-0.552	0-0(0)

Table 2 provides the summary of the primary and secondary memberships obtained for EO_L for the emotion: disgust. For each feature we obtain 5 Tables like Table 2, each one for a given emotion. Thus for 5 features, we would have altogether 25 such tables. In Table 2, we also computed the product of primary and secondary memberships, and then obtain the minimum and maximum of the product to determine its range, as indicated in the last column of Table 2.

The range for each feature corresponding to individual emotions is given in Table 3. For example, the entry (0-0.14) corresponding to the row Anger and column EO_L, gives an idea about the extent of the EO_L for the unknown subject matches with known subjects from the emotion class Anger. The results of computing fuzzy meet operation over the range of individual features taken from facial expressions of the subjects under same emotional condition are given in Table 3. The average of the ranges along with its centre value is also given in Table 3. It is observed that the centre has the largest value (=0.2775) for the emotion: happiness

5 Conclusion

The paper employs GT2FS-based automatic emotion recognition of an unknown facial expression, when the background knowledge about a large face database with known emotion class are available. The GT2FS-based recognition scheme requires type-2 secondary membership distributions, a computation of which by an evolutionary approach is also provided. The scheme first construct a fuzzy face space, and then infer the emotion class of the unknown facial expression by determining the maximum support of the individual emotion classes using the pre-constructed fuzzy face space. The class with the highest support is regarded as the emotion of the unknown facial expression. The scheme, however, takes care of both the inter- and intra-subject level uncertainty, and thus offers a higher classification accuracy for the same set of features. Experimental analysis confirms that the classification accuracy of emotion by employing GT2FS is 96.67%.

References

1. Uwechue, O.A., Pandya, S.A.: Human Face Recognition Using Third-Order Synthetic Neural Networks. Kluwer, Boston (1997)
2. Biswas, B., Mukherjee, A.K., Konar, A.: Matching of digital images using fuzzy logic. AMSE Publication 35(2), 7–11 (1995)
3. Bhavsar, A., Patel, H.M.: Facial Expression Recognition Using Neural Classifier and Fuzzy Mapping. In: IEEE Indicon 2005 Conference, Chennai, India (2005)
4. Guo, Y., Gao, H.: Emotion Recognition System in Images Based on Fuzzy Neural Network and HMM. In: Proc. 5th IEEE Int. Conf. on Cognitive Informatics (ICCI 2006). IEEE (2006)
5. Rizon, M., Karthigayan, M., Yaacob, S., Nagarajan, R.: Japanese face emotions classification using lip features. In: Geometric Modelling and Imaging (GMAI 2007), Universiti Malaysia Perlis, Jejawi, Perlis, Malaysia. IEEE (2007)
6. Kobayashi, H., Hara, F.: Measurement of the strength of six basic facial expressions by neural network. Trans. Jpn. Soc. Mech. Eng. (C) 59(567), 177–183 (1993)
7. Ekman, P., Friesen, W.V.: Unmasking the Face: A Guide to Recognizing Emotions From Facial Clues. Prentice-Hall, Englewood Cliffs (1975)
8. Mendel, J.M.: On the importance of interval sets in type-2 fuzzy logic systems. In: Proc. Joint 9th IFSA World Congress 20th NAFIPS Int. Conf., Vancouver, BC, Canada, July 25-28, pp. 1647–1652 (2001)
9. Chakraborty, A., Konar, A., Chakraborty, U.K., Chatterjee, A.: Emotion Recognition From Facial Expressions and Its Control Using Fuzzy Logic. IEEE Transactions on Systems, Man and Cybernetics (2009)
10. Das, S., Halder, A., Bhowmik, P., Chakraborty, A., Konar, A., Nagar, A.K.: Voice and Facial Expression Based Classification of Emotion Using Linear Support Vector. In: 2009 Second International Conference on Developments in eSystems Engineering. IEEE (2009)