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A Fuzzy-Convolution Model for Physical Action and Behaviour Pattern Recognition of 3D Time Series

Theodoros Theodoridis and Huosheng Hu
Department of Computing and Electronic Systems, University of Essex
Wivenhoe Park, Colchester CO4 3SQ, U.K.
{ttheod, hhu}@essex.ac.uk

***Abstract*— In this paper an innovative model architecture is proposed based on the fusion of a multi auto-adjusted TSK fuzzy logic classifier and a signal convolver classifier to model physical actions and behaviours without any giving prior knowledge of the modeled activities. Three different hypotheses are being tried to investigate such as the classification accuracy of 3D time series activity data, the discrimination clarity of a novel convolution classifier, and a vast number of experimental testing to tune the classifiers' internal structure by revealing optimal configuration attributes such as features, distances, and functions. The fuzzy-convolution model is being used by a mobile robot for remote surveillance within a smart environment. The hardware configuration incorporates an ubiquitous 3D marker based tracker which establishes an interface between the robot and the actor. The data form is time series based which is fetched to the robot throughout an off-line process.**

***Index Terms*— Pattern Classification, Action Recognition, Fuzzy Classifiers, Signal Convolution.**

I. INTRODUCTION

Modeling and classifying physical actions is a task which has received a lot of attention by many researchers in pattern recognition on the field of intelligent surveillance. Fuzzy logic has been extensively used for pattern recognition but less in action recognition of time series data. On the other hand, convolution is being addressed as a method used in signal processing as well as in computer vision whereas in pattern classification has got very poor interest. In this work an attempt has been tried to merge these two approaches by introducing a fuzzy-convolution model for action A = $\{$standing^1, handshaking^2, waving^3, clapping^4, pushing^5, pulling^6, slapping^7, kicking^8, punching$^9\}$ and behaviour B = $\{$normal^1, aggressive$^2\}$ recognition respectively by testing a number of internal attribute configurations of the classifiers.

In literature, an approach for intrusion detection and the discrimination of normal and abnormal behaviours has been proposed by [1]. The approach generates fuzzy classifiers using genetic algorithms. In [1], anomaly is detected by analyzing the changes of a normal behavioural pattern to provide discriminant characteristics. A feature-entropy based fuzzy classifier proposed by [2], employs fuzzy entropy to evaluate distribution of recognized patterns without the use of a rule base. [3] discussed about a fuzzy "black-box" approach with unknown mathematical model $g(.)$ and measurable input/output parameters such as triangular membership functions. A heuristic fuzzy miner method for the classification of numerical data without defuzzification has been used by [4]. The approach can automatically generate fuzzy if-then rules to determine an unknown transfer function between an attribute space and a given class from numerical data. Fuzzy clustering of short time series using a new distance method (STS) has been proposed by [5] to measure similarities of patterned shapes. The distance method presented, can provide information of similarities between two time series by measuring the difference of slopes. Alternatively, a method to mine periodic patterns in time series signals with unknown or obscure periods has been discussed by [6]. This problem has been attempted to be solved using convolution of shifted signals in order to mine patterns with one pass.

Fig. 1 illustrates the hardware configuration setting of the system architecture used in this project. A person is shown to act in a 3D intelligent environment performing some physical activity. Two external devices, a 3D tracker (Vicon system) and a mobile robot (SCITOS G5), cooperate as a perception to action unit to produce classification statistics of action and behaviour recognition [7].

The rest of the paper is organized as follows: In section II, the fuzzy-convolution model architecture is analyzed where a fuzzy TSK model and a convolution classification algorithm explained analytically as well as tuning attributes and methods are presented for the model's internal configuration. Experimental results are shown in section III whereas section IV points out conclusions and future work.

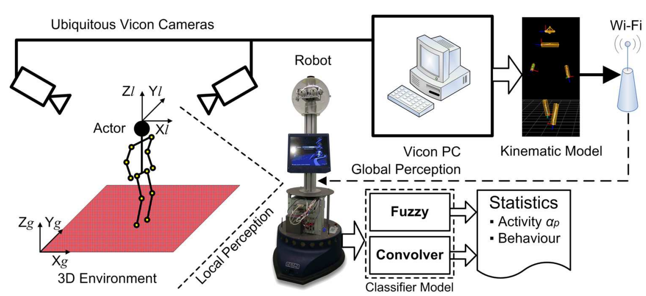


Fig. 1. Configuration setting showing an actor's physical activity, within a 3D ubiquitous environment, tracked by a mobile to robot.

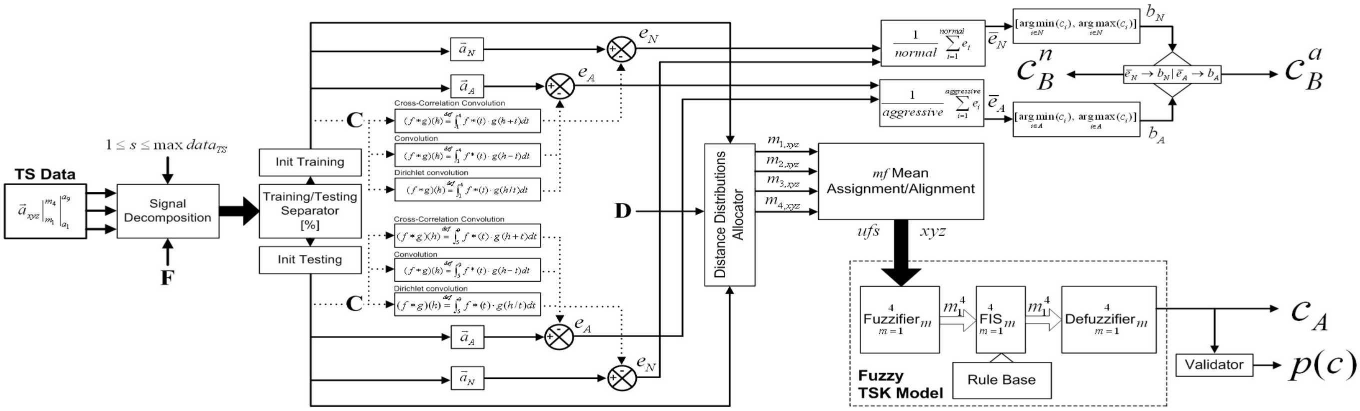


Fig. 2. The Fuzzy-Convolution model.

II. FUZZY-CONVOLUTION MODEL

The core element of this architecture is depicted in Fig. 2 where is shown a functional partitioning of the Fuzzy-Convolution model. The model's structural design consists of two main classifiers each used to provide classification indications of a recognized physical activity. The human-actor which performs physical activity is monitored by the 3D tracker through four reflectable markers aligned on the limbs [7]. The source which provides information, generated in time series, is shown on the left side of the diagram where we see the *TS Data* module which is the raw time series provider allocating activity data lists in 3D vectors for each of the four markers, times the nine physical actions to be identified. The *Signal Decomposition* module acquires the raw time series and decomposes them into timestamp-segments. The number of segments s can be $1 \leq s \leq maxdata_{TS}$, where $maxdata$ is the length of a time series TS. Each segmented timestamp is thereafter used to be reformed by a feature attribute, taken from the configuration matrix $\mathbf{F}$ (see Table I), which is a significant representation of all the data values accounted in each segment. The need of using such a module is for dimensionality reduction as well as to filter noise-corrupted chunks of a segment, as discussed in [2], achieving thus higher classification accuracy by making the classifiers more discriminant. The next module, *Training/Testing Separator*, allocates the training percentage (=50%) and the testing percentage (=50%) to be used for classification.

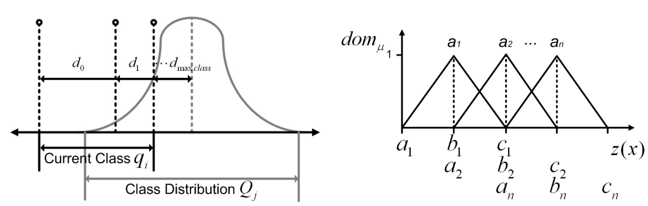
A. FLC Classifier

The main classification method of the model is an auto-adjusted multi fuzzy logic classifier (FLC) utilized to map action pattern time series into individual classes by generating distances from the input membership functions $\mu_F^{inp}s$ (see Fig. 3(a)). Unlike to a number of research projects such a in [4][1][8] that use adaptive processes to derive, generate, or extract fuzzy rules so that to achieve optimal mapping between the input/output spaces, we demonstrate how a small number of fixed linear rules can derive high classification accuracy by using the training data to auto-adjust the $\mu_F^{inp}s$.

The multi FLC architecture consists of four typical TSK models (each for a marker) with three inputs each and a common rule base for all the four classifiers. This multiple classifier design merges both classifier categories: *classifier selection* and *classifier fusion* as referred by [8]. More analytically, the selection method reveals the classifier with the best classification accuracy which is going to be the one selected to provide an output. On the other hand, classifier fusion is also employed to account all the classification results so that to provide a probability of validity of a recognized class.

There are nine $\mu_F^{inp}s$, one for each physical action. The $\mu_F^{inp}s$ are auto-adjusted according to the magnitude of the training data. The output membership functions $\mu_F^{out}s$ are singletons allocated on the support area as the number of class-actions $A = \{1, 2, ..., 9\}$ indicate. The rule base consists of nine rules implementing linear mapping which is a straight connection of an input to its corresponded output μ_F^{out}. With conventional nonlinear mapping the rule base should have had $\mu_F^{INP}s = 27$ rules.

1) Auto Adjusted Input mFs: Auto-adjustment is an adaptation of the input fuzzy sets $\mu F^{inp}s$ to fit the training data. Initially, preprocessing is employed by taking the training data and computing the distance distributions of a particular



(a) (b)

Fig. 3. (a) Class distribution diagram showing distance d_i extraction, (b) Input fuzzy membership function indicating the mean-based alignment.

class comparing each individual class with all the rest. In Fig. 2, the *Distance Distribution Allocator* module calculates $D_{m_c} = \{A_{m_c} - 1\}$ distances for each action from the action set A, marker m, and coordinate c. The general diagram of Fig. 3(a) depicts the acquisition of the distances from a current class q_i compared with its distribution Q_j. Equation 1 shows how the distance distribution is computed from an action vector $\vec{a}$ of marker m and coordinate c.

$$d\vec{a}_{m,c} = \sum_{i=1}^{n} \sum_{j=1}^{n-1} (q_i^{\vec{a}_{m,c}} \ominus Q_j^{\vec{a}_{m,c}}) \quad (1)$$

where symbol $\ominus$ represents a distance method taken from the configuration matrix **D** containing a number of distances (see Table II) used to test the classifiers performance.

The resultant information of the acquired distance distributions passes to the *mF Mean Assignment/Alignment* module so that to fit the distributions into input $\mu_F s$. Each of the nine actions has a unique μ_F whereas each FLC input represents one of the three coordinates. Thus, the system's overall setting has an FIS with a rule base of nine rules, MISO (multi input, single output) system, and nine triangular $\mu_F^{inp} s$ as used in [3]. Initially, the module performs assignment where the mean of each distance distribution is assigned to the central b point of a membership triangle shown by Equation 2.

$$\mu F_j^i triangle_{\vec{a}}(b) \leftarrow \bar{d\vec{a}}_{m,c} \quad (2)$$

where from the fuzzy set $F_{j=1..u}^{i=1..U}$, U is the rule number, and u denotes the dimension of the input space [9].

After the assignment of the mean values to the central of the $\mu_F s$, mean alignment is performed by assigning the central b points to a and c points of the adjacent $\mu_F s$. In Fig. 3(b) we can see the alignment of the three points for each μ_F. Having the values of the b points only, we calculate the a and the c adjacent points: $\mu_{F_1}\{a_1 = b_2 - b_1, c_1 = b_2\}$, $\mu_{F_2}\{a_2 = b_1, c_2 = b_n\}$, $\mu_{F_n}\{a_n = b_2, c_n = b_2 + b_n\}$.

2) Fuzzy TSK Model: Similar to [3], the TSK classifier model consists of three principal elements where action recognition is performed as Fig. 2 depicts.

1) **Fuzzifier** The fuzzifier consists of triangular fuzzy sets μF_j^i with support and core areas described by Equations 3 and 4 respectively, and the degree of membership μ_i (DOM) given by 5:

$$s_{F_j^i} := \{x_j : \mu_{F_j^i}(x_j) > 0\} \forall a \leq x \leq c \quad (3)$$

$$c_{F_j^i} := \{x_j : \mu_{F_j^i}(x_j) = 1\} \forall x = b \quad (4)$$

$$\mu_F(x) = \begin{cases} 0, & x \leq a \\ \text{x-a/b-a}, & x \in (a,b), a \leq x \leq b \\ \text{c-x/c-b}, & x \in (b,c), b \leq x \leq c \\ 0, & x \geq c \end{cases} \quad (5)$$

The fuzzification process estimates the activation weight, of all μ_i, by Equation 6:

$$\mu_i(x) = \prod_{j=1}^{u} \mu_{F_j^i}(x_j) \quad (6)$$

2) **FIS** The mapping of the input/output fuzzy sets is implemented by the FIS [9] where each rule establishes an input/output linear mapping by giving a different degree of membership for each class-mapping [5]. The formation of a linear rule is given by Equation 7:

$$\Re_i : \; if \; x_j \; is \; A_j^i \; then \; z = c_i, \quad \forall \; c_i \subset A_j^i \quad (7)$$

where $c_i \subset A_j^i$ denotes a linear connection of the output class c_i being a class of the subset class A_j^i without common support characteristics ($c^s \neq A^s$).

3) **Defuzzifier** For performance issues the Singleton defuzzification method has been selected. The output fuzzy sets $\mu F^{out} s$ are singletons and because they lack from support area this type is expressed by its unique core point a, $\forall \; a = x$ similar to Equation 4. With such fuzzy sets the weighted-average defuzzifier is given by Equation 8, where $apex_i$ denotes the output recommended by the rule i.

$$z(x) = \left[\sum_{i=1}^{U} \mu_{F_j^i}(x_j) \cdot apex_i \right] / \left[\sum_{i=1}^{U} \mu_{F_j^i}(x_j) \right] \quad (8)$$

B. Convolver Classifier

A behaviour expresses characteristics which are inherited from actions that project a certain activity; in other words, a behaviour includes a group of actions. Based on this assumption, behaviours can be discriminated and recognized when a single action is compared with an action behavioural group so that to assess whether there is significance. The anomaly detection problem of a behaviour to be discriminated as normal or abnormal, discussed by [1], is addressed by accounting the distance of a particular sequence of activity and comparing it with a given threshold. In contrast with [1], we address the problem by manifesting the notion of convolving all the actions which belong to a certain behaviour, by combining their expression signal-time series, so that to produce a unique signal which should expresses characteristics from all the actions of a particular group.

Three convolution methods are contained in the configuration matrix **C**: *Cross-Correlation*, *Convolution*, *Dirichlet Convolution*. The dashed lines in Fig. 2 denote that each of these three convolution methods can be selected to test the model's performance. The $\vec{a}_N$ and $\vec{a}_A$ define the normal and the aggressive activity vectors respectively which are compared with the convoluted signals to generated an average error $\bar{e}_{N/A}$, similar to the problem appeared in [6] which

TABLE I

FEATURE INDEX

F	C	Name	Formula
1	Central Tendency	Mean	$mean(x) = \frac{1}{n} \cdot \sum_{i=1}^{n} x_i$
2		Interquartile Mean	$iqm(x) = \frac{2}{n} \sum_{i=(n/4)+1}^{3n/4} xi$
3		Generalized Mean	$gnm(x, p) = \left(\frac{1}{n} \sum_{i=1}^{n} x_i^p\right)^{1/p}$
4		Harmonic Mean	$hrm(x) = n/\left(\sum_{i=1}^{n} \frac{1}{x_i}\right)$
5		Geometric Mean	$gom(x) = \left(\prod_{i=1}^{n} x_i\right)^{1/n}$
6		Root Mean Square	$rms(x) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} x_i^2}$
7		Mean Absolute Value	$mav(x) = \frac{1}{n} \cdot \sum_{i=1}^{n} \lvert x_i \rvert$
8		MAV Slope	$mavs(x) = mav_1^{n/2} - mav_{n/2}^{n}$
9		Mid-Range	$mdr(x) = (x_{max} + x_{min})/2$
10	Variational	Standard Deviation	$sdv(x) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)^2}$
11		Variance	$var(x) = \frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)^2$
12		Skewness	$ske(x) = \sum_{i=1}^{n} (x_i - \mu)^3/(n-1)\sigma^3$
13		Kurtosis	$kur(x) = \sum_{i=1}^{n} (x_i - \mu)^4/(n-1)\sigma^4$
14		Error Propagation	$(x) = (1/\sqrt{n})\ \sigma$
15	Waveformal	Waveform Length	$wl(x) = \sum_{i=1}^{n-1} \lvert x_{i+1} - x_i \rvert$
16		Zero Crossing	$zc(x) = \sum_{i=1}^{n-1} f_i$ $f_i = \begin{cases} 1 & x_i\ x_{i+1} < 0 \text{ and } \lvert x_i - x_{i+1} \rvert < x_{th} \\ 0 & \text{otherwise} \end{cases}$
17		Slope Sign Changes	$ssc(x) = \sum_{i=2}^{n-1} f_i$ $f_i = \begin{cases} 1 & x_i > x_{i-1} \text{ and } x_i > x_{i+1} \text{ or } x_i < x_{i-1} \text{ and } x_i < x_{i+1} \text{ and } \lvert x_i - x_{i+1} \rvert < x_{th} \text{ or } \lvert x_i - x_{i-1} \rvert < x_{th} \\ 0 & \text{otherwise} \end{cases}$
18		Willison Amplitude	$wamp(x) = \sum_{i=1}^{n-1} f(x_i - x_{i+1})$ $f(x) = \begin{cases} 1 & x > x_{th} \\ 0 & \text{otherwise} \end{cases}$
19	Extremal	Minimum	$min(x) = argmin_{i \in S}\{s_i\}$
20		Maximum	$max(x) = argmax_{i \in S}\{s_i\}$
21		Summing	$sum(x) = \sum_{i=1}^{n} x_i$

Indicators*

TABLE II

DISTANCE INDEX

D	C	Name	Formula
1	Distance	Rounded Hamming	$rhm(s_1, s_2) = \sum_{i=1}^{n} x_i$ $x_i = \begin{cases} 1 & \lvert \lfloor s_{1_i} \rfloor - \lfloor s_{2_i} \rfloor \rvert \\ 0 & \text{otherwise} \end{cases}$
2		Short Time Series	$sts(s_1, s_2) = \sum_{i=0}^{n} \left(\frac{s_{2_{i+1}} - s_{2_i}}{(i+1)-1} - \frac{s_{1_{i+1}} - s_{1_i}}{(i+1)-1}\right)^2$
3		Euclidean	$euc(s_1, s_2) = \sqrt{\sum_{i=1}^{n} (s_{1_i} - s_{2_i})^2}$
4		Mahalanobis Norm.	$mne(s_1, s_2) = \sqrt{\sum_{i=1}^{n} \frac{(s_{1_i} - s_{2_i})^2}{\sigma_{1_i}^2}}$
5		Bregman Divergence	$brd(s_1, s_2) = \sum_{i=1}^{n} s_{1_i} log(s_{1_i}/s_{2_i})$
6		Normalized Google	$ngd(s_1, s_2) = nom/den$ $nom = log(n) - min\{logf[\Sigma(s_1)], logf[\Sigma(s_2)]\}$ $den = max\{logf[\Sigma(s_1)], logf[\Sigma(s_2)]\} - logf[\Sigma((s_1 + s_2)/2)]$
7		Chebyshev	$chd(s_1, s_2) = \sum_{i=1}^{n} max_i(\lvert s_{1_i} - s_{2_i} \rvert)$
8		Lee	$lee(s_1, s_2, q) = \sum_{i=1}^{n} min\{\lvert s_{1_i} - s_{2_i} \rvert, q - \lvert s_{1_i} - s_{2_i} \rvert\}$
9	Error	Error	$err(s_1, s_2) = \sum_{i=1}^{n} (s_{1_i} - s_{2_i})$
10		Absolute	$abs(s_1, s_2) = \sum_{i=1}^{n} \lvert s_{1_i} - s_{2_i} \rvert$
11		Square Error	$sqr(s_1, s_2) = \sum_{i=1}^{n} (s_{1_i} - s_{2_i})^2$
12		Mean Square Error	$mse(s_1, s_2) = \frac{1}{n} \sum_{i=1}^{n} (s_{1_i} - \mu_1)^2 - (s_{2_i} - \mu_2)^2$
13	Correlational	Pearson's Coeff.	$mcv(s_1, s_2) = \frac{\sum_{i=1}^{n} (s_{1_i} - \mu_1)(s_{2_i} - \mu_2)}{n \sigma_1 \sigma_2}$
14		Kendall-tau	$ktd(s_1, s_2) = \sum_{i=1}^{n} x_i/[(n(n-1))/2]$ $x_i = \begin{cases} 1 & (s_{1_i} < s_{1_{i+1}}) \text{ and } (s_{2_i} > s_{2_{i+1}}) \\ 0 & \text{otherwise} \end{cases}$
15		Spearman's rank Coeff.	$src(s_1, s_2) = 1 - \frac{6 \sum_{i=1}^{n} (s_{1_i} - s_{2_i})^2}{n(n^2 - 1)}$
16	Statistical	Chi-squared	$chi(s_1, s_2) = \sum_{i=1}^{n} (s_{1_i} - s_{2_i})^2/\sigma^2$
17		Z-test	$zts(s_1, s_2) = \sum_{i=1}^{n} \frac{(s_{1_i} - s_{2_i}) - (\mu_1 - \mu_2)}{\sqrt{(\sigma_1^2 + \sigma_2^2)/n}}$
18		T-test	$tts(s_1, s_2) = \sum_{i=1}^{n} \frac{(s_{1_i} - s_{2_i}) - (\mu_1 - \mu_2)}{(\sigma_1^2 - \sigma_2^2)/\sqrt{n}}$
19	Probabilistic	Probability Distribution	$pdd(s_1, s_2) = 2 \frac{\lvert \mu_1 - \mu_2 \rvert}{\sigma_1 + \sigma_2}$
20		Total Variation	$tvd(s_1, s_2) = \frac{1}{2} \sum_{i=1}^{n} \lvert s_{1_i} - s_{2_i} \rvert$
21		Bhattacharyya	$bhd(s_1, s_2) = \sum_{i=1}^{n} \sqrt{s_{1_i} \cdot s_{2_i}}$
22		Hellinger	$hel(s_1, s_2) = \frac{1}{2} \sqrt{\lvert 2 - (2 \cdot bhd) \rvert}$

Indicators*

TABLE III

CONVOLUTION FUNCTION INDEX

C	C	Name	Formula
1	Convolution	Norm. X-correlation	$ncc(f * g) = \frac{(f(t) - \mu_f)(g(t) - \mu_g)}{\sigma_f \sigma_g}$
2		Convolution	$con(f * g)(h) = \sum_A f(t) g(h - t)$
3		Dirichlet	$dir(f * g)(h) = \sum_A f(t) g(h/t)$

Indicators*

* '*C*' category, 's, f, g' signal time series, 'x' data list, 'μ' the mean, 'σ' standard deviation, 'n' max data, 'c' max classes, 'k' the lag, 'h' signal shifting coefficient, 't' time step, 'p' non-zero real number, 'th' threshold

compares modified, through shifting, signals with the original signals to result a matched pattern. Thereafter, the average error passes through a boundary $b_{N/A}$ check to decide which behaviour is identified $\bar{e}_N \rightarrow b_N : c_B^n$ (normalBehaviour), $\bar{e}_A \rightarrow b_A : c_B^a$ (aggressiveBehaviour). The following algorithm shows more analytically the classification convolution:

Algorithm *Convolver Classifier*

$h = 0$

$\vec{c}_{nrm_{trn/tst}} \leftarrow (f * g)(h) \stackrel{def}{=} \int_1^4 f * (t) \cdot g(h - t) dt$

$\vec{c}_{agg_{trn/tst}} \leftarrow (f * g)(h) \stackrel{def}{=} \int_5^9 f * (t) \cdot g(h - t) dt$

$\bar{e}_{nrm_{trn/tst}} \leftarrow \frac{1}{n} \sum_{t=1}^{n} \left| \vec{c}_{nrm_{trn/tst_t}} - \vec{a}_{nrm_{trn/tst_t}} \right|$

$\bar{e}_{agg_{trn/tst}} \leftarrow \frac{1}{n} \sum_{t=1}^{n} \left| \vec{c}_{agg_{trn/tst_t}} - \vec{a}_{agg_{trn/tst_t}} \right|$

behaviour1 $\leftarrow$
if $\bar{e}_{nrm_{tst}} \geq argmin_{i \in N}\{\bar{e}_{nrm_{trn}}\}$ & $\bar{e}_{nrm_{tst}} \leq argmax_{i \in N}\{\bar{e}_{nrm_{trn}}\}$
behaviour2 $\leftarrow$
elseif $\bar{e}_{agg_{tst}} \geq argmin_{i \in N}\{\bar{e}_{agg_{trn}}\}$ & $\bar{e}_{agg_{tst}} \leq argmax_{i \in N}\{\bar{e}_{agg_{trn}}\}$
$NULL \leftarrow$ **else**

where vectors $\vec{c}_{nrm_{trn/tst}}$ and $\vec{c}_{agg_{trn/tst}}$ are the training and the testing normal and aggressive convolved signals, whereas $\vec{a}$ and $\bar{e}$ are the raw signals and the average errors.

C. Architectural Attributes

The internal structure of the fuzzy-convolution model can be tuned by testing several architectural attributes selected from the configuration matrices so that to optimize the classification performance and the discrimination clarity. There are three configuration matrices: **F**(21×1) containing time domain feature attributes (see Table I), **D**(22×1) consisting of distance attributes (see Table II), and **C**(3×1) including convolution function attributes used by the convolver classifier only (see Table III). All matrices are shown in Fig. 2 which have been used to modify the classifiers internal structure so that to achieve distinct recognition accuracy.

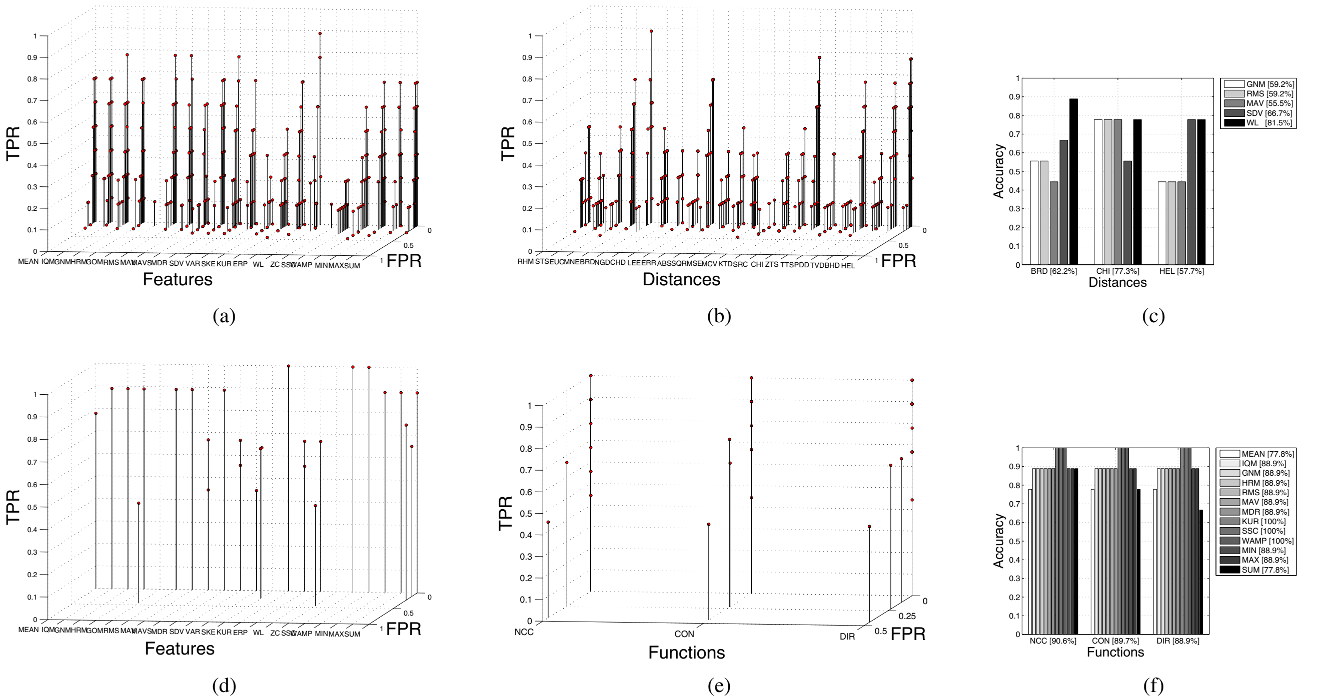


Fig. 4. (a) FLC feature ROC diagram, (d) Convolver feature ROC diagram, (b) FLC distance ROC diagram, (e) Convolver function ROC diagram. (c) FLC derived best attributes, (f) Convolver derived best attributes.

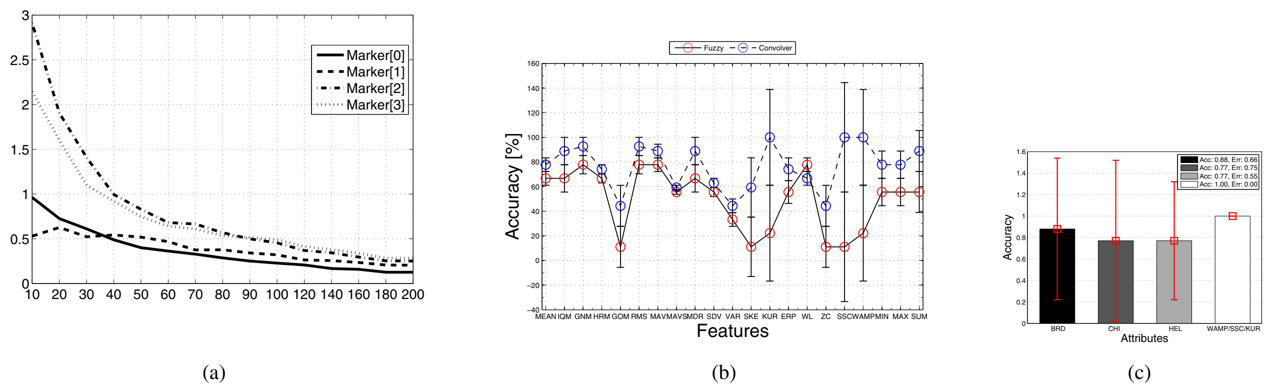


Fig. 5. (a) Data dispersion performance throughout 15 signal segmentations using the Coefficient of Dispersion (COD), (b) Classifier overall performance tested on the whole feature space, (c) Best attribute performances.

III. EXPERIMENTAL RESULTS

Similar to the principle of structural risk minimization (SRM) [8], the selected attributes derived from the classifiers' accuracy, are chosen according to the smallest misclassification error. Furthermore, the selected attributes must lead the classifiers to achieve reasonably good accuracy which has been thresholded to $\geq 70\%$, and small deviation of the classification's error stated as recognition divergence.

Initially, it is being examined which is the appropriate number of segments to decompose a signal time series so that the classifier not to overfit the data. Thereby, the statistical Coefficient of Dispersion (COD), Equation 9, has been applied to a number of different segmented lengths of a signal shown in Fig. 5(a), where the plotted COD values denote that if the coefficient is less than one then the data set is under-dispersed. Basically, the smallest the COD the less the dispersion is which is a fact that increases the probability of a data set to have formed a significant cluster. Fig. 5(a) illustrates an averaged performance of the COD values of all the available data set shown on the *TS Data* module of Fig. 2. Eventually, 100 segments was the length selected since for ≥ 100 segments the COD is being stabilized.

$$cod = \sigma^2/\mu \tag{9}$$

In the next experiment (Fig. 5(b)), 462 runs averaged the performance of the fuzzy classifier, testing all the feature space versus the distance space whereas 63 runs averaged the performance of the convolver classifier, testing all the feature space versus the function space. From these configurations tested (525 in overall), the fuzzy classifier appears to overcome the threshold in the following feature categories: *central tendency*, *variational*, and *waveformal*, whereas the convolver classifier appears to have at least one distinct feature in all categories. To see the attribute performance more analytically, four ROC diagrams shown in Fig. 4 reveal which attributes achieved distinct results. Fig. 4(c) and 4(f) summarize the average percentages of the ROC performance of the attributes which overcame the predefined threshold. Thereafter, the three best attributes are being selected to lead the classifiers to optimal classification. To test this, a number of performance measures, depicted in Table IV, are being applied to the classification results for further analysis. For the fuzzy classifier, feature WL performed best for all the three distances BRD, CHI, and HEL. Likewise, for the convolver classifier the NCC function performed best for the features WAMP, SSC, and KUR.

From the results illustrated in Table IV, we observe that Bregman's Divergence distance provides the highest performance measures such as: relevancy validation of the classification (precision), proportional completeness validation of the classification (recall), class recognition (accuracy), discrimination clarity (F-Measure), and discrimination power (D-Power). On the other hand, the convolver classifier got exceptional accuracy for all the three features tested with the Normalized Cross Correlation convolution.

Ultimately, the last test is to measure the classifiers' validation error where for the fuzzy classifier such validation can be obtained by averaging the true positive classes recognized by all the individual classifiers, whereas for the convolver classifier an even more discrete method has been applied by assigning *true* for a correct class, *false* for a misclassification, and $1/2$ otherwise. Figure 5(c) illustrates the attribute error bars from which we see that the distinct distances are coming from different groups (see table II) with dominant the BRD which achieved average error of 0.66, meaning that approximately more than two markers have been recognized in overall for all the actions.

Waveformal and Central Tendency features have been proved as the ones which provide close to optimal performance, from the classification perspective. There is though no common characteristic of these two categories since the former deals with the waveform, the slope, and the amplitude of a signal whereas the later focuses on several variations of the mean value of a distribution.

IV. Conclusions and Future Work

An innovative fuzzy-convolution model has been presented as the core architecture of a surveillance robot/system which can provide classification statistics, in terms of actions and behaviours, of an actor acting within an intelligent environment. The model is decomposed in two major classifier architectures: an auto-adjusted multi fuzzy classifier used for action recognition, and a convolver classifier used for behaviour discrimination. Moreover, a vast number of attributes utilized as configuration parameters to optimize the model's classification performance. Eventually, the fuzzy-convolution model can provide good quality recognition statistics trustworthy for the surveillance task. Eventually, the outcome derived from this analysis is that the fuzzy-convolution model can provide good quality recognition statistics with validation evaluation making it trustworthy for the surveillance task.

In future, we are going to extend this research by studying forces of mechanical features taken from Kinematics, Dynamics, Elasticity, and Energy.

TABLE IV

Best Feature/Distance/Function Performance Measures

Fuzzy Classifier						
$\mathbf{D}_{WL}$	$error$ **CLASSES**	**Precision**	**Recall**	**Accuracy**	**F-Measure**	**D-Power**
BRD	1: 0.50, 2: 0.75, 3: 0.75, 4: 0.25, 5: 0.75, 6: 0.75, **5**: 1.00, 8: 0.75, 9: 0.50	0.83	0.88	0.88	0.85	4
CHI	1: 0.50, 2: 0.50, 3: 0.75, 4: 1.00, **9**: 1.00, 6: 0.75, **0**: 1.00, 8: 0.75, 9: 0.50	0.72	0.77	0.77	0.74	3
HEL	1: 0.00, 2: 0.50, 3: 0.50, 4: 0.50, 5: 0.50, 6: 0.75, **9**: 0.75, **0**: 1.00, 9: 0.50	0.72	0.77	0.77	0.74	3
Convolver Classifier						
$\mathbf{F}_{NCC}$	$error$ **CLASSES**	**Precision**	**Recall**	**Accuracy**	**F-Measure**	**D-Power**
WAMP/SSC/KUR	1: 0.0, 1: 0.0, 1: 0.0, 1: 0.0, 2: 0.0, 2: 0.0, 2: 0.0, 2: 0.0, 2: 0.0	1.0	1.0	1.0	1.0	4

$^{D_{WL}}$ $Tested\, distances\, \mathbf{D}\, with\, feature\, WL.$
$^{F_{NCC}}$ $Tested\, features\, \mathbf{F}\, with\, function\, NCC.$

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