# Taking Refuge in Your Personal Sentic Corner

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## Abstract

In a world in which web users are continuously blasted by ads and often compelled to deal with user-unfriendly interfaces, we sometimes feel like we want to evade from the sensory overload of standard web pages and take refuge in a safe web corner, in which contents and design are in harmony with our current frame of mind. Sentic Corner is an intelligent user interface that dynamically collects audio, video, images and text related to the user's current feelings and activities as an interconnected knowledge base, which is browsable through a multi-faceted classification website.

#### 1 Introduction

In normal human cognition, thinking and feeling are mutually present - our emotions are often the product of our thoughts as well as our reflections are frequently the product of our sentiments. Emotions, in fact, are intrinsically part of our mental activity and play a key role in decision-making processes. They are special states shaped by natural selection to balance the reaction of our organism to particular situations, e.g., anger evolved for reaction, fear evolved for protection and affection evolved for reproduction.

In the new realm of Web 2.0 applications, the analysis of emotions has undergone a large number of interpretations and visualizations (We-FeelFine, 2011; Moodviews, 2011; Moodstats, 2011; Moodstream, 2011), which have often led to the development of emotion-sensitive systems and applications. Nonetheless, today web users still have to almost continuously deal with sensoryoverloaded web pages, pop-up windows, annoying ads, user-unfriendly interfaces, etc. Moreover, even for websites uncontaminated by web spam, the affective content of the page is often totally unsynchronized with the user's emotional state. Web pages containing multimedia information inevitably carry more than just informative content. Behind every multimedia content, in fact, there is always an emotion. Sentic Corner exploits this concept to build a sort of parallel cognitive/affective digital world in which the most relevant multimedia contents associated to the users' current moods and activities are collected, in order to enable them, whenever they want to evade from sensory-rich, overwrought and earnest web pages, to take refuge in their own safe web corner.

The structure of the paper is the following: Section 2 presents related work on managing affective multimedia contents, Section 3 describes the AI and Semantic Web tools exploited within this work, Section 4 explains in detail the techniques and the methods hereby used to retrieve and manage semantically and affectively relevant multimedia contents, Section 5 illustrates the overall process for the creation of the affective multimedia environment, Section 6 presents an evaluation of the adopted tools and, eventually, Section 7 comprises concluding remarks and a description of future work.

#### 2 **Related Work**

To our knowledge, there is still no published study on the task of automatically retrieving and displaying multimedia contents according to user's moods and activities, although the affective and semantic analysis of video, audio and textual contents have been separately investigated extensively (Srinivasan et al., 2005; Hanjalic, 2006; Schleicher et al., 2010; Cambria et al., 2011a). The most relevant commercial tool within this area is Moodstream (Moodstream, 2011), a mashup of several forms of media, designed to bring users music, images, and video according to the mood they manually select on the web interface. Moodstream aims to create a sort of audio-visual ambient mix that can be dynamically modified by users by selecting from the presets of 'inspire', 'excite', 'refresh', 'intensify', 'stabilize', and 'simplify', e.g., mixtures of mood spectra on the Moodstream mixer such as happy/sad, calm/lively or warm/cool. Users can start with a preset and then mix things up including the type of image transition, whether they want more or less vocals in their music selection and how long images and video will stay, among other settings.

In Moodstream, however, songs are not played entirely but blended into one another every 30 seconds and, even if the user has control on the multimedia flow through the mood presets, he/she cannot actually set a specific mood and/or activity as a core theme for the audio-visual ambient mix. Sentic Corner, on the contrary, uses sentic computing (Cambria et al., 2010b), a new paradigm for the affective analysis of text, to automatically extract semantics and sentics, i.e., the cognitive and affective information, associated with user's status updates on micro-blogging websites and, hence, to retrieve relevant multimedia contents in harmony with his/her current emotions and motions.

# **3** Sentic Computing

Sentic computing has been recently proposed as a multi-disciplinary approach to opinion mining and sentiment analysis that exploits both computer and social sciences to better recognize, interpret and process opinions and sentiments over the Web. Specifically, sentic computing involves the use of AI and Semantic Web techniques, for knowledge representation and inference; mathematics, for carrying out tasks such as graph mining and multi-dimensionality reduction; linguistics, for discourse analysis and pragmatics; psychology, for cognitive and affective modeling; sociology, for understanding social network dynamics and social influence; finally ethics, for understanding related issues about the nature of mind and the creation of emotional machines.

In sentic computing, the analysis of text is based on common sense reasoning tools and affective ontologies. Differently from statistical classification, which generally requires large inputs and thus cannot appraise texts with satisfactory granularity, sentic computing enables the analysis of documents not only on the page or paragraph-level but also on the sentence and clause-level. Within this work, in particular, we use a novel emotion categorization model (section 3.1), a language visualization and analysis system (section 3.2) and a web ontology for human emotions (section 3.3).

## 3.1 The Hourglass of Emotions

The Hourglass of Emotions (Cambria et al., 2010c) is a novel affective categorization model in which sentiments are organized around four independent dimensions, whose different levels of activation make up the total emotional state of the mind. The Hourglass of Emotions, in fact, is based on the idea that the mind is made of different independent resources and that emotional states result from turning some set of these resources on and turning another set of them off (Minsky, 2006).

The primary quantity we can measure about an emotion we feel is its strength. But when we feel a strong emotion it is because we feel a very specific emotion. And, conversely, we cannot feel a specific emotion like 'fear' or 'amazement' without that emotion being reasonably strong. Mapping this space of possible emotions leads to an hourglass shape (Fig. 1).



Figure 1: The Hourglass of Emotions

The Hourglass of Emotions is specifically designed to recognize, understand and express emotions in the context of human computer interaction (HCI). In the model, in fact, affective states are not classified, as often happens in the field of emotion analysis, into basic emotional categories, but rather into four independent and concomitant dimensions, Pleasantness, Attention, Sensitivity and Aptitude, in order to understand how much respectively the user is happy with the service provided, interested in the information supplied, comfortable with the interface and disposed to use the application. Each affective dimension, in particular, is characterized by six levels of activation (measuring the strength of an emotion), termed 'sentic levels', which determine the intensity of the expressed/perceived emotion as an  $int \in [-3,3]$ .

These levels are also labeled as a set of 24 basic emotions (Plutchik, 2001), six for each of the affective dimensions, in a way that allows the model to specify the affective information associated with text both in a dimensional and in a discrete form. The dimensional form, in particular, is called 'sentic vector' and it is a four-dimensional *float* vector that can potentially express any human emotion in terms of Pleasantness, Attention, Sensitivity and Aptitude.

## 3.2 AffectiveSpace

AffectiveSpace (Cambria et al., 2009) is a multidimensional vector space built from ConceptNet (Havasi et al., 2007), a directed graph representation of common sense knowledge, and WordNet-Affect (Strapparava and Valitutti, 2004), a linguistic resource for the lexical representation of affective knowledge.

In particular, we use truncated singular value decomposition (TSVD) (Wall et al., 2003) in order to obtain a new matrix containing both hierarchical affective knowledge and common sense. The resulting matrix has the form  $\tilde{A} = U_k \Sigma_k V_k^T$  and is a low-rank approximation of A, the original data. This approximation is based on minimizing the Frobenius norm of the difference between A and  $\tilde{A}$  under the constraint  $rank(\tilde{A}) = k$ . For the Eckart–Young theorem it represents the best approximation of A in the mean-square sense, in fact:

$$\min_{\tilde{A}|rank(\tilde{A})=k} |A - \tilde{A}| = \min_{\tilde{A}|rank(\tilde{A})=k} |\Sigma - U^* \tilde{A} V|$$
$$= \min_{\tilde{A}|rank(\tilde{A})=k} |\Sigma - S|$$

assuming that  $\tilde{A}$  has the form  $\tilde{A} = USV^*$ , where S is diagonal. From the rank constraint, i.e., S has k non-zero diagonal entries, the minimum of the above statement is obtained as follows:

$$\min_{\tilde{A}|rank(\tilde{A})=k} |\Sigma - S| = \min_{s_i} \sqrt{\sum_{i=1}^n (\sigma_i - s_i)^2} = \\= \min_{s_i} \sqrt{\sum_{i=1}^k (\sigma_i - s_i)^2 + \sum_{i=k+1}^n \sigma_i^2} = \sqrt{\sum_{i=k+1}^n \sigma_i^2}$$

Therefore,  $\hat{A}$  of rank k is the best approximation of A in the Frobenius norm sense when  $\sigma_i = s_i$ (i = 1, ..., k) and the corresponding singular vectors are same as those of A. If we choose to discard all but the first k principal components, common sense concepts and emotions are represented by vectors of k coordinates: these coordinates can be seen as describing concepts in terms of 'eigenmoods' that form the axes of AffectiveSpace, i.e., the basis  $e_0,...,e_{k-1}$  of the vector space (Fig. 2).

For example, the most significant eigenmood,  $e_0$ , represents concepts with positive affective valence. That is, the larger a concept's component in the  $e_0$  direction is, the more affectively positive it is likely to be. Concepts with negative  $e_0$  components, then, are likely to have negative affective valence. Thus, by exploiting the information sharing property of TSVD, concepts with the same affective valence are likely to have similar features - that is, concepts conveying the same emotion tend to fall near each other in AffectiveSpace. For example we can find concepts such as 'beautiful day', 'birthday party', 'laugh' and 'make person happy' very close in direction in the vector space, while concepts like 'sick', 'feel guilty', 'be laid off' and 'shed tear' are found in a completely different direction (nearly opposite with respect to the center of the space).

#### 3.3 The Human Emotion Ontology

The Human Emotion Ontology (HEO) (Grassi, 2009) is conceived as a high level ontology for human emotions that supplies the most significant



Figure 2: AffectiveSpace

concepts and properties, which constitute the centerpiece for the description of every human emotion. The main purpose of HEO is to create a description framework that could grant at the same time enough flexibility, by allowing the use of a wide and extensible set of descriptors to represent all the main features of an emotion, and interoperability, by allowing to map concepts and properties belonging to different emotion representation models.

HEO has been developed in ontology web language description logic (OWL DL) for its expressiveness and its inference power in mapping the different models used in the emotion description. OWL DL, in fact, allows a taxonomical organization of emotion categories and properties restriction in order to link emotion description made both by category and by dimension.

## 4 Corner Deviser

The main aim of the Corner Deviser is to process the semantics and sentics obtained through sentic computing in order to retrieve relevant multimedia contents from the Web and, hence, encode these in a Semantic Web aware format. In particular, the cognitive and affective information is processed through a technique that performs inference over multiple sources of data (section 4.1), a statistical method for the identification of common semantics (section 4.2), a technique that expands semantics through spreading activation (section 4.3).

The resulting semantics and sentics are then exploited to pull relevant music (Section 4.4), videos (Section 4.5), images (Section 4.6) and text (Section 4.7) from the Web and, eventually, encode these in RDF/XML (Section 4.8).

### 4.1 Blending

Blending (Havasi et al., 2009) is a technique that performs inference over multiple sources of data simultaneously, taking advantage of the overlap between them. It basically combines two sparse matrices linearly into a single matrix in which the information between the two initial sources is shared. When we perform SVD on a blended matrix, the result is that new connections are made in each source matrix taking into account information and connections present in the other matrix, originating from the information that overlaps.

By this method, we can combine different sources of general knowledge, or overlay general knowledge with domain-specific knowledge, such as medical, geological or financial knowledge.

### 4.2 CF-IOF Weighting

CF-IOF (concept frequency - inverse opinion frequency) (Cambria et al., 2010a) is a technique that identifies common domain-dependent semantics in order to evaluate how important a concept is to a set of opinions concerning the same topic.

Firstly, the frequency of a concept c for a given domain d is calculated by counting the occurrences of the concept c in the set of available dtagged opinions and dividing the result by the sum of number of occurrences of all concepts in the set of opinions concerning d. This frequency is then multiplied by the logarithm of the inverse frequency of the concept in the whole collection of opinions, that is:

$$CF\text{-}IOF_{c,d} = \frac{n_{c,d}}{\sum_k n_{k,d}} \log \sum_k \frac{n_k}{n_c}$$

where  $n_{c,d}$  is the number of occurrences of concept c in the set of opinions tagged as d,  $n_k$  is the total number of concept occurrences and  $n_c$  is the number of occurrences of c in the whole set of opinions. A high weight in CF-IOF is reached by a high concept frequency in a given domain and a low frequency of the concept in the whole collection of opinions.

#### 4.3 Spectral Association

Spectral association (Havasi et al., 2010) is a technique that involves assigning values to 'seed concepts' and applying an operation that spreads their values across the ConceptNet graph. This operation, an approximation of many steps of spreading activation, transfers the most activation to concepts that are connected to the key concepts by short paths or many different paths in common sense knowledge. In particular, we build a matrix C that relates concepts to other concepts, instead of their features, and add up the scores over all relations that relate one concept to another, disregarding direction.

Applying C to a vector containing a single concept spreads that concept's value to its connected concepts. Applying  $C^2$  spreads that value to concepts connected by two links (including back to the concept itself). But what we would really like is to spread the activation through any number of links, with diminishing returns, so the operator we want is:

$$1 + C + \frac{C^2}{2!} + \frac{C^3}{3!} + \ldots = e^C$$

We can calculate this odd operator,  $e^C$ , because we can factor C. C is already symmetric, so instead of applying Lanczos' method to  $CC^T$  and getting the SVD, we can apply it directly to C and get the spectral decomposition  $C = V\Lambda V^T$ . As before, we can raise this expression to any power and cancel everything but the power of  $\Lambda$ . Therefore,  $e^C = Ve^{\Lambda}V^T$ . This simple twist on the SVD lets us calculate spreading activation over the whole matrix instantly. As with the SVD, we can truncate these matrices to k axes and therefore save space while generalizing from similar concepts.

### 4.4 Sentic Tuner

The module for the retrieval of semantically and affectively related music is called Sentic Tuner. The relevant audio information is pulled from Stereomood, an emotional on-line radio that provides music that best suits users' mood and activities (Stereomood, 2011). In the web interface, music is played randomly through an on-line music player with the possibility for the user to play/stop/skip tracks.

In Stereomood, music tracks are classified according to some tags that users are supposed to manually choose in order to access a list of semantically or affectively related songs. These tags are either mood-tags (e.g., 'happy', 'calm', 'romantic', 'lonely' and 'reflective') or activity-tags (such as 'reading', 'just woke up', 'dressing up', 'cleaning' and 'jogging'), the majority of which represent cognitive and affective knowledge contained in AffectiveSpace as common sense concepts and emotional labels. The Sentic Tuner uses the moodtags as centroids for blending and the activity-tags as seeds for spectral association, in order to build a set of affectively and semantically related concepts respectively, which will be used at run-time to match the concepts extracted from user's microblogging activity. The Sentic Tuner also contains a few hundreds  $r\bar{a}gas$  (Sanskrit for moods), which are melodic modes used in Indian classical music meant to be played in particular situations (mood, time of the year, time of the day, weather conditions, etc.).

It is considered inappropriate to play  $r\bar{a}gas$  at the wrong time (it would be like playing Christmas music in July, lullabies at breakfast or sad songs at a wedding) so these are played just when semantics and sentics exactly match time and mood specifications in the  $r\bar{a}gas$  database. Hence, once semantics and sentics are extracted from natural language text through sentic computing, Stereomood API and the  $r\bar{a}gas$  database are exploited to select the most relevant tracks to user's current feelings and activities.

### 4.5 Sentic TV

Sentic TV is the module for the retrieval of semantically and affectively related videos. In particular, the module pulls information from Jinni, a new site that allows users to search for video entertainment in many specific ways (Jinni, 2011).

The idea behind Jinni is to reflect how people really think and talk about what they watch. It is based on an ontology developed by film professionals and new titles are indexed with an innovative natural language processing (NLP) technology for analyzing metadata and reviews. In Jinni, users can choose from movies, TV shows, short films and on-line videos to find specific genres or what they are in the mood to watch. In particular, users can browse videos by topic, mood, plot, genre, time/period, place, audience and praise. Similarly to the Sentic Tuner, Sentic TV uses Jinni's mood-tags as centroids for blending and the topic-tags as seeds for spectral association in order to retrieve affectively and semantically related concepts respectively.

Time-tags and location-tags are also exploited in case relevant time-stamp and/or geo-location information is available within user's microblogging activity.

## 4.6 Sentic Slideshow

Sentic Corner also offers semantically and affectively related images through the Sentic Slideshow module. Pictures related to the user's current mood and activity are pulled from Fotosearch (Fotosearch, 2011), a provider of royalty free and rights managed stock photography which claims to be the biggest repository of images on the Web. Since Fotosearch does not offer a priori mood-tags and activity-tags, the CF-IOF technique is used on a set of 1000 manually tagged (according to mood and topic) tweets (Twitter, 2011), in order to find seeds for spectral association (topic-tagged tweets) and centroids for blending (mood-tagged tweets).

Each of the resulting concepts is used to retrieve mood and activity related images through the Fotosearch search engine. The royalty free pictures, eventually, are saved in an internal database according to their mood and/or activity tag, in a way that they can be quickly retrieved at run-time, depending on user's current feelings and thoughts.

# 4.7 Sentic Library

The aim of Sentic Library is to provide book excerpts depending on user's current mood. The module proposes random book passages users should read according to the mood they should be in while reading it and/or what mood they will be in when they have finished. The excerpt database is built according to '1001 Books for Every Mood: A Bibliophile's Guide to Unwinding, Misbehaving, Forgiving, Celebrating, Commiserating' (Ephron, 2008), a guide in which the novelist Hallie Ephron serves up a literary feast for every emotional appetite.

In the guide, books are labeled with mood-tags such as 'for a good laugh', 'for a good cry' and 'for romance', but also some activity-tags such as 'for a walk on the wild side' or 'to run away from home'. As for Sentic TV and Sentic Tuner, Sentic Library uses these mood-tags as centroids for blending and the topic-tags as seeds for spectral association.

# 4.8 Encoding

In order to effectively represent the retrieved audio, video, visual and textual multimedia information, we encode it in a Semantic Web aware format and store it in a Sesame triple-store, a purposebuilt database for the storage and retrieval of RDF metadata (Sesame, 2009).

Sesame can be embedded in applications and used to conduct a wide range of inferences on the information stored, based on RDFS and OWL type relations between data. In addition, it can also be used in a standalone server mode, much like a traditional database with multiple applications connecting to it. In particular, we encode the data in RDF/XML using the descriptors defined by HEO and insert them into the triple-store, in a way that multimedia contents can be queried and results can be retrieved in a semantic aware format.

# 5 Sentic Corner Generation Process

The process for creating Sentic Corner comprises five main components (Fig. 3): a NLP module, which performs a first skim of the real-time fetched user tweets, a Semantic Parser, whose aim is to extract concepts from the lemmatized text, AffectiveSpace, for the extraction of semantics and sentics from the given concepts, the Corner Deviser, which exploits the cognitive and affective information obtained to retrieve and encode relevant multimedia, and the Exhibit (Exhibit, 2011) intelligent user interface (IUI), for the visualization of results.

In particular, the NLP module interprets all the affective valence indicators usually contained in tweets such as special punctuation, complete upper-case words, onomatopoeic repetitions, exclamation words, negations, degree adverbs and emoticons, and eventually lemmatizes text.

The Semantic Parser then deconstructs text into concepts and provides, for each of them, the relative frequency, valence and status, i.e., the concept's occurrence in the text, its positive or negative connotation, and the degree of intensity with which the concept is expressed.

The AffectiveSpace module projects the retrieved concepts into the vector space clustered wrt the Hourglass model sentic levels using a kmedoids approach (Cambria et al., 2011b), and infers the affective valence of these, in terms



Figure 3: Sentic Corner Generation Process

of Pleasantness, Attention, Sensitivity and Aptitude, according to the positions they occupy in the space. The Corner Deviser exploits the semantic and sentic knowledge bases previously built by means of blending, CF-IOF and spectral association to find matches for the concepts extracted by the Semantic Parser and their relative affective information inferred by AffectiveSpace.

Such audio, video, visual and textual information (namely Sentic Tuner, Sentic TV, Sentic Slideshow and Sentic Library) is then encoded in RDF/XML according to HEO and stored in the triple-store. In case the sentics detected belong to the lower part of the Hourglass, the multimedia contents searched will have an affective valence opposite to the emotional charge detected, as Sentic Corner aims to restore the positive emotional equilibrium of the user, e.g., if the user is angry he/she might want to calm down.

The Exhibit IUI module, eventually, visualizes the contents of the Sesame database exploiting the multi-faceted categorization paradigm. Faceted classification allows the assignment of multiple categories to an object, enabling classifications to be ordered in multiple ways, rather than in a single taxonomic order. This allows to perform searches combining the textual approach with the navigational one. Faceted search, in fact, enables users to navigate a multi-dimensional information space by both writing queries in a text box and progressively narrowing choices in each dimension. For Sentic Corner, in particular, we use SIMILE Exhibit API, a set of Javascript files that allows to easily create rich interactive web-pages including maps, timelines and galleries, with very detailed client-side filtering. Exhibit pages use the multifaceted classification paradigm to display semantically structured data stored in a Semantic Web aware format, e.g., RDF or JavaScript object notation (JSON). One of the most relevant aspects of Exhibit is that, once the page is loaded, the web-browser also loads the entire data set in a lightweight database and performs all the computations (sorting, filtering, etc.) locally on the client-side, providing high performances.

The information contained in the triple-store is exported to the Exhibit IUI as a JSON file in order to make the data available for being browsed as a unique knowledge base (Fig. 4). In the web interface, multimedia contents are displayed in a dynamic gallery, which can be ordered according to mood and activity tags (in case they are not unique) plus other parameters such as title, genre, source, modality, etc.

The IUI allows to explore such information both by using the search box, to perform keywordbased queries, and by filtering the results using the faceted menus, i.e., by adding or removing constraints on the facet properties. The extracted affective information, moreover, is exploited to modify the design of the webpage in a way that the user always feels comfortable with the interface. If positive affective information is extracted, for example, a design with smooth edges windows and hot colors is adopted.

# 6 Evaluation

In order to test Sentic Corner's affect recognition capabilities, we evaluated the system with a corpus of mood-tagged blogs from LiveJournal (LJ) (LiveJournal, 2011), a virtual community of more than 23 millions users who keep a blog, journal or diary. One of the interesting features of this website is that LJ bloggers are allowed to label their posts with a mood tag, by choosing from more than 130 predefined moods or by creating custom mood themes. Since the indication of the affective status is optional, the mood-tagged posts are likely to reflect the true mood of the authors and, hence, form a good test-set for Sentic Corner.

In order to have full correspondence between LJ mood labels and Hourglass sentic levels, a pool of 10 students have been asked to map each of the 130 mood labels into the 24 emotional labels of the Hourglass model. All LJ accounts have Atom, RSS and other data feeds which show recent public entries, friend relationships and interests. Unfortunately, there is no possibility to get mood-tagged blog-posts via data feeds so we had to design our own crawler.

After retrieving and storing relevant data and metadata from 10,000 LJ posts, we extracted sentics through the Sentic Corner Generation Process and compared the output with the relative moodtags, in order to calculate statistical classifications such as precision and recall. On average, each post contained around 140 words and, from it, about 4 affective valence indicators and 60 sentic vectors were extracted. According to this information, we assigned mood-labels to each post and compared these with the corresponding LJ mood-tags, obtaining very good accuracy for each of the mapped moods.

Among these, 'happy' and 'sad' posts were identified with particularly high precision (89% and 81% respectively) and decorous recall rates (76% and 68%). The F-measure values obtained, hence, were significantly good (82% and 74% respectively), especially if compared to the corresponding F-measure rates of the baseline methods (53% and 51% for keyword spotting, 63% and 58% for lexical affinity, 69% and 62% for statis-



Figure 4: Sentic Corner web interface

tical methods). In the future, we plan to perform also some usability tests in order evaluate the relevance of contents and design displayed, together with the overall user-friendliness of the interface.

# 7 Conclusion and Future Work

Today an average web user spends around 15 hours per week surfing the Net. Since most of the profit on the Web revolves around advertisement, users are too often blasted with sensoryoverloaded web pages, pop-up windows and annoying ads. Within this work, we merged AI and Semantic Web techniques to build an intelligent user interface that dynamically collects audio, video, images and text related to the user's current feelings and activities as an interconnected knowledge base, which is browsable through a multifaceted classification website.

Sentic Corner exploits the concept that behind every multimedia content there is always an emotion to build a sort of parallel cognitive/affective digital world in which all the multimedia contents are in harmony with user's current emotions and motions. Eventually, Sentic Corner represents a first step towards the development of sentic interfaces, i.e., next-generation intelligent applications capable of perceiving and expressing the cognitive and affective information associated with user interaction.

# 8 Acknowledgments

This work was undertaken during the first author's research visit to the National Laboratory of Pattern Recognition (NLPR), Institute of Automation, Chinese of Academy of Sciences (CAS) in Beijing (China), which was jointly funded by the Royal Society of Edinburgh (UK) and CAS.

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